The Simulation of Social Exchange: Developing a Multidimensional Model of Exchange Rules in Human Interaction

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Declaration

Submitted in fulfilment of the requirements for the degree of Master of Social Science (Psychology), in the Discipline of Psychology, University of KwaZulu-Natal, Pietermaritzburg, South Africa.

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Abstract

Social exchange underpins social structure and as such, social exchange theory has taken a central role in the field of social psychology. The study of exchange rules and how they interact with each other is an area within this theory that has not received much attention up until now. This study has aimed to study the exchange rules of fairness, reciprocity, self-interest, vicinity and ingroup favouritism within an interacting exchange network. Agent based computational modelling with a comparison to empirical data has been proposed as a novel method to uncover the process of exchange from the bottom up. The results of the study indicate that there exists no universal combination of exchange rules that can predict human behaviour in all settings. Exchange rules are adopted based on institutional norms as well as norms that emerge during interaction.

Acknowledgments

This thesis is dedicated to Yahweh

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Chapter 1: Introduction

Social exchange is an important component of interaction between individuals. Most people are likely to go through many exchanges in a single day. For this reason, the study of social exchange under the banner of social exchange theory has been at the forefront of social psychology for nearly half a century. Social exchange theory can be traced back to the early 20th century but was most notably introduced by George Homans in 1958. Homans (1958) was interested in the microprocesses of social exchange and how that led to the formation of macrosocial structure. He argued that individuals weigh up cost and rewards when deciding on potential exchanges. His assumption of rationality has been argued by many, yet the theoretical groundwork that he laid has held.

Cropanzano and Mitchell (2005) highlighted the valid point that social exchange theory has great explanatory power for understanding human interaction but that it suffers from areas of conceptual ambiguity and a general lack of fully specified core conceptualisations. One area, according to Cropanzano and Mitchell (2005), that has suffered a great lack of research within the social exchange framework is the area of exchange rules. Exchange rules according to Meeker (1971) are the normative guidelines that direct decisions made by individuals in exchange situations.

Drawing from recent empirical literature on the motivations behind exchange behaviour, this research has set out to resurrect the important groundwork that Meeker laid by proposing a reconceptualised model of social exchange with the specific exchange rules of reciprocity, ingroup favouritism, self-interest, fairness and proximity. A random giving exchange rule was added to these five in order to account for careless or uncertain decision making.

Research on these exchange rules have largely been done one rule at a time or at most two (Cropanzano & Mitchell, 2005). This means that the expected interaction between these exchange rules has not been assessed.

A potential reason for the shortage of research on the interaction of exchange rules is the methodological difficulties in studying the process of exchange. Computational agent-based modelling has been proposed in the current research as a methodology that can effectively model exchange behaviour from agent level decision making.

Using every combination between exchange rules at three levels of each rule, 729 simulations were run in total. The results of the agent-based model have then been quantitatively compared to empirical data derived from human experiments in order to validate the simulated results. The particular exchange rules or combinations of exchange rules used in the most accurate simulations are used to indicate the particular exchange rules that were used by human participants in the laboratory experiment.

Chapter 2: Literature review

Social Exchange Theory

Social exchange theory, most notably defined by Homans (1958) is a theory that attempts to describe social structure as the product of microsocial exchanges between individuals. In this theory, it is assumed that individuals, when faced with a potential exchange, will calculate the costs and rewards of the exchange so as to maximise gains and minimize costs.

The early work of Homans focussed on sub-institutional exchange processes and attempted to explain larger social structures as a product of microsocial behaviour (Cook, Cheshire, Rice, & Nakagawa, 2013). His claim was that emergent social phenomena can always be explained by attributes of individuals in interaction. His work was eventually deemed overly reductionistic as it did not take into account larger institutional influences that shape microsocial behaviour. In addition to this, it did not take into account the macrosocial phenomena that emerges from social interaction which simply cannot be reduced to the actions of individuals (Cook et al., 2013). The work of Blau (1968) and Emerson (1976) evolved this theory to account for these shortfalls.

Social exchange theory has gone on to explain dynamics within exchange networks such as power (structural inequality between groups or individuals), commitment, emotion and fairness considerations as a few examples of forces that shape exchange within networks (Cook et al., 2013). In short, larger cultural and contextual norms, as well as institutional forces, can shape exchange behaviour and the resulting emerged macrosocial structure.

In the original conception of social exchange theory, rationality was assumed. This posits that individuals will make rational decisions regarding the outcomes of an exchange. Conflicting occurrences of irrational behaviour, such as revenge seeking where individuals incur a cost if it means getting back at another, led Meeker (1971) to argue against the assumed rationality that underpins exchange decisions. She argued for a far narrower conception of rationality whereby individuals are rational in that they will evaluate consequences of an exchange but not necessarily aim for profit maximisation (Meeker, 1971). This thinking led to the theory of exchange as individual decisions guided by a framework of rules that are relied upon for making decisions regarding the mode of exchange.

Rules of exchange

Exchange relationships are formed by exchange, and for this exchange to take place there need be a set of rules that guide and govern exchange. These “exchange rules” are normative prescriptions for behaviour that guide the exchange process between individuals (Cropanzano & Mitchell, 2005). A simple example of an exchange rule, and the one most frequently relied upon in exchange research, is reciprocity. Reciprocity is a rule that influences an individual to return kind favours directed towards them during past exchange.

Meeker (1971) argued that exchanges between individuals can be considered as individual decisions and that these decisions require a set of rules to guide decision making. In this logic, she specified six decision rules of altruism, ingroup gain, status consistency, competition and reciprocation. These rules are further elaborated on below.

- Altruism can be defined as a decision rule that has the aim of rewarding another individual even if that means a complete cost to the giver.
- Ingroup gain, as defined by Meeker (1971), is a rule that leads to the maximum reward for all individuals concerned. This can be thought of as a common storehouse of resources that individuals use as needed. This decision rule then does not include interpersonal exchange.
- Status consistency is a rule that seeks to maintain the status that exists before the exchange begins. This decision rule then uses the logic of individual A having a higher payoff in an exchange than individual B if individual A has a higher status at the beginning of the exchange.
- Competition is a rule that seeks the maximum difference in payoffs between individuals in an exchange. This can even mean a reduced reward for the giver if it means harming the receiver.

- Reciprocation is a rule that seeks to reward past acts of kindness. This rule maintains a cooperative set of exchanges.

Meeker (1971) argues that these exchange rules are not mutually exclusive, and that more than one rule can be adopted at one time if they are in line with the particular goal structure. For example, an individual could adopt a rule of altruism and ingroup gain without any conflict between rules. A few questions are generated from Meeker's framework, the first being; what contextual factors lead to combinations of decision rules being adopted? Another question that is highlighted is; what factors induce preference to one rule over another and what facilitates the shift from one rule to another?

Answering these questions requires specific focus on the normative and structural context in which the interaction is imbedded. Exchange rules are either sanctioned or inhibited by a contextual or larger social norm. If we consider rationality that has been a popular assumption in social exchange theory, we would argue that an individual would seek the decision rule that would allow them the maximum payoff with little regard of the consequences for the exchange partner. This would be in line with the homo-economicus model which assumes pure rationality with no social constraints to profit maximisation. As discussed later in this review, this behaviour can exist, but is seldom seen empirically. One reason for this is that self-interest is often constrained by conflicting norms. For example, if in a certain context there exists a social norm that punishes selfishness, it would then force the individual to adopt an exchange rule that accrues the largest benefit without being deemed selfish. Using this logic, one could also logically conclude that a decision rule that is highly competitive would not be suitable in a context where fairness to the poor is highly esteemed. In this context, an individual would likely adopt an exchange rule that gives preference to giving to the poor. An exchange rule that fosters cooperation, such as reciprocity, may also be suitable in this context.

The fundamental tension between rationality and exchange rules that are normatively prescribed by the context constitute an institutional force that will alter microsocial exchange as well as emergent macrosocial phenomena. The implications of the lack of research in this area are that competition between rules under different circumstances are not fully understood, nor are the cases when multiple exchange rules are used in combinations.

The current research is aimed at studying the process of exchange with focus on which exchange rules individuals adopt in different contexts. This research will focus on microlevel interindividual exchange and how this emerges into a larger social structure.

Toward a reconceptualised set of exchange rules

Research on exchange rules has evolved substantially since Meeker's original contribution, and a reconceptualised model is warranted. A large literature from the field of economics, sociology and social psychology has sought to understand the psychological motivations of exchange behaviour. This research has generally studied exchange rules in isolation. Though the empirical support for these mechanisms is given, the current research will aim to study how these interact with each other. Drawing on this literature, there has been much empirical evidence for reciprocity, ingroup favouritism, fairness or inequity aversion, proximity and self-interest. The following section of the review will focus on detailing recent empirical support for each of these proposed exchange rules.

Reciprocity

Reciprocation in its essential form is the behavioural response by a recipient to an action targeted towards them. The response could be positive, such as a reward for kindness, or it could take a negative form which would entail punishment for an unkind action (Falk & Fischbacher, 2006). This section will outline the decision-making process involved in reciprocation as well as outline the theoretical components of reciprocation in social exchange.

Reciprocation is a fundamental component of social organisation and is a powerful driving force behind behaviour (Falk & Fischbacher, 2006). Gouldner (1960) goes so far as to argue that reciprocity is a universal mechanism that can be found in every culture. Gouldner (1960) in fact wrote the famous quote:

"A norm of reciprocity is, I suspect, no less universal and important an element of culture than the incest taboo, although, similarly, its concrete formulations may vary with time and place." (p. 171).

The manner in which reciprocity presents itself and the determinates of how one should reciprocate will differ in different contexts and social spheres. The universal component of reciprocation as argued by Gouldner (1960) can be summarised in two basic rules; the first being that individuals should repay kind acts that have been directed towards them, and the second being that individuals should not harm those that have acted kindly towards them.

At this point it is necessary to distinguish two conceptually different forms of reciprocation. The first of these two, and indeed the more traditional understanding of reciprocation, is known as direct reciprocity. This type of reciprocity is a simple ‘tit for tat’ reciprocation, or, as Nowak and Sigmund (2005) quite succinctly define it; “you scratch my back and I will scratch yours” (p. 1).

The second form of reciprocation is known as indirect reciprocity, and this is defined as the type of reciprocation where a receiver will not directly reciprocate to the giver, but to someone else. In this mode of reciprocation, a giver is likely to give to any agent that has been seen to help others in the past (Nowak & Sigmund, 1998). Indirect reciprocity is more focussed on reputation with the avoidance of negative consequences (Nowak & Sigmund, 2005).

In the current research, focus is directed towards interaction between multiple exchange rules and mathematical tractability is of concern. For this reason, only direct reciprocity will be of focus.

The best-known research on direct reciprocation is the work of Axelrod (1984), in which reciprocation was studied using the game ‘the prisoners dilemma”. This research will be briefly detailed below.

The prisoner’s dilemma

The prisoner’s dilemma is a simple game that entails two players. Each player has a choice of whether to cooperate with the other player or to defect. The players must choose their course of action without knowing what the other player will do. If player 1 chooses to defect and player 2 chooses to cooperate, player one will have a higher pay off than if he/she had chosen to cooperate. The dilemma is introduced when both players choose to defect, if they select defection their payoff will be less than if they had cooperated.

In order to study the emergence of cooperation through reciprocation, Axelrod developed a research design that took the form of a tournament. Participants were mostly professors from the fields of economics, mathematics, psychology and sociology. Each participant was tasked with developing a rule that would be used to model strategies in the prisoner’s dilemma game. All strategies were able to use history in order to make future choices. Strategies submitted varied between highly complex rules that aimed at maximum long-term payoff to simple rules that mimicked the opponents previous move. Each participant was paired with an opponent in one condition, as well as a condition in which they would oppose a clone. For a theoretical baseline, the participant was also paired with a random strategy that randomly chose either to defect or to cooperate in each round.

Two trials were held and in both trials the strategy “tit for tat” was the strategy that accrued the highest average number of points. This strategy was a simple rule that cooperated (didn’t defect) in the first round and then reciprocated in either a positive or negative way in every proceeding round. The success derived through this simple strategy was due to a few behavioural traits that it possessed. The first of these was that it was kind. This strategy would never be the player to defect first. It set a baseline of initial cooperation, but if crossed, it would be quick to punish by defecting in the subsequent round. Tit for tat was very forgiving, after its initial retaliation, it would forgive and forget all previous cheating. The forgiveness was a critical component to its success as it fostered and restored cooperation between players.

The research conducted by Axelrod (1984) clearly demonstrated the dramatic effect that reciprocity has in guiding behaviour in social settings. A limitation of this study is that reciprocity is studied in dyadic relationships. In real world situations, individuals have a far greater population of people that they are able to interact with. If an individual were to be faced with cheating in a larger group, it is likely that they would punish the opponent by taking their business elsewhere, thereby removing any chance of future interaction.

Increased wealth vs underlying intentions

A factor of reciprocation that warrants discussion is the motivational factors when deciding on reciprocating. When evaluating a token exchange, there are two main factors that would lead to reciprocation, the individual would either base their response on the increased wealth or the perceived intentions of the generous giver (Falk & Fischbacher, 2006).

The simpler of the two would be the increased wealth obtained through the token exchange. This could be a powerful determinate for reciprocation which would become more important as the receiving agent's wealth decreases.

The second factor would be the intentions behind the token allocation. This incorporates both the increase in wealth as well as the social meaning behind the giving. The interpretation of the intentions behind the token allocation will then prove to be a large deciding factor in whether or not to reciprocate (Keysar, Converse, Wang, & Epley, 2008).

Recent empirical evidence has suggested that the perceived intentions of a helpful action from one individual to another has a large impact on the degree to which people are inclined to engage in direct reciprocity (Orhun, 2018). If the original giver is deemed to be self-interested and not altruistic in their behaviour, people are less likely to reciprocate.

Ingroup favouritism

Ingroup favouritism, the tendency to favour one's own group and to discriminate against the outgroup, is a robust phenomenon in social exchange. Nearly a century of research has aimed to uncover and explain the determinants of this behaviour. In this section of the review, a brief overview of historical research will be discussed, following that, current research exploring ingroup favouritism will be reviewed.

The realistic conflict studies had the aim of assessing the development of ingroup favouritism in response to competition for resources. It was hypothesised that competition for resources between groups would lead to participants discriminating against the outgroup and favouring the ingroup (Sherif, Harvey, White, Hood, &

Sherif, 1988). It was further hypothesised that this conflict could be reduced through cooperation.

The experiment started with a formation phase where participants were placed into groups and were given goals that would foster cooperation between group members. This phase led to the formation of a common sense of group membership. The second phase introduced competitive activities with the promise of the winning group receiving a prize. The introduction of competition quickly led to outgroup derogation and a strengthening of ingroup favouritism. The groups became more cohesive and more polarized from each other.

The study led by Sherif, Harvey, White, Hood, and Sherif (1961) was instrumental in demonstrating the effect that competition can have on a sense of group identity and ingroup favouritism. Tajfel, Billig, Bundy, and Flament (1971) argued that competition was not necessary for the formation of ingroup favouritism and discriminatory behaviour targeted towards the outgroup. Instead, they argued that the mere classification of a group and one's membership in this group could lead to ingroup favouritism and discrimination towards the outgroup. Tajfel et al. (1971) successfully demonstrated this theory with the minimal group studies.

In this pioneering study, Tajfel and his team used a novel method to introduce knowledge of one's group with the most minimal salience. They set out to find the baseline condition upon which the social categorization and resulting ingroup intergroup discrimination would take place. In order to study ingroup favouritism with a minimal group setting, three criteria had to be enforced (Otten, 2016). Firstly, the categorization had to be arbitrary and the groups had to be new, meaning they may not have had any other previous experience with these group boundaries. Secondly, interaction had to be eliminated to remove extraneous variables such as reciprocation. Thirdly, self-interest had to be constrained in order to accurately measure ingroup favouritism instead of selfishness (Otten, 2016). Participants were requested to choose between two paintings and were then told that they were assigned to a group based on their choice. They were in fact randomly assigned to the two groups. Each participant in isolation used pen and paper tasks that consisted of a set of matrices in which they could allocate monetary rewards to either the ingroup or the outgroup, and in some cases, a proportion between both.

The results of the study indicated that the process of social categorization was adequate in producing discriminatory behaviour targeted towards the outgroup and a tendency to favour the ingroup. Tajfel (1970) originally postulated that ingroup bias emerges due to individuals having learnt, through social interaction, to favour the ingroup. When confronted with a novel group situation, individuals will then transfer this norm of ingroup favouritism into the new group. Thus, this hypothesis implies a generic and persistent norm of ingroup favouritism, a kind of innate psychological mechanism that is initiated with the most minimal suggestion of group belonging (Iacoviello & Spears, 2018). This hypothesis was later abandoned by Tajfel and replaced by the social identity theory which explained the emergence of ingroup favouritism being driven by a need for a positive self-concept derived from belonging to a group (Tajfel & Turner, 1979).

Research conducted by Iacoviello and Spears (2018), aimed to revisit Henry Tajfel's generic norm hypothesis by designing a study that investigated ingroup favouritism as a result of participants relying on a pre-existing norm of favouring the ingroup when faced with a novel and uncertain group, as well as a group in a naturalistic setting.

The research was split into two separate studies, the first study was focussed on assessing attitudes and perceptions towards ingroup favouritism in a natural group. The second study had the same aim of assessing attitudes and perceptions but also assessed allocation behaviour within the minimal group paradigm.

In study one, Participants were required to answer test items that used national political groups as the group to which participants may identify with. A measure of attitudes towards ingroup favouritism and the participants perceptions of norms that related to favouring the ingroup were obtained using tests within the self-presentation paradigm. This is an attitude scale that firstly measures participants attitudes toward ingroup favouritism, and secondly measures how the norm of ingroup favouritism was perceived. In order to determine how participants perceive a norm, a series of test questions were given where they had to respond to all the items under three different conditions. The first condition required that participants answer all test items as they are. In the second condition, participants were given the instruction to answer all items in a manner that a reader would positively regard them (self-enhancement). The third condition required participants to answer all items in a manner that a reader would negatively regard them (self-depreciation). This method allows researchers to distinguish whether a norm is promoted externally, if the self-enhancement scores are higher, or promoted internally, if the self-depreciation scores are higher.

The results of this first study indicate that participants perceive the generic ingroup norm as one that would promote ingroup favouritism (Iacoviello & Spears, 2018). This suggests that participants have a default norm, learnt through prior interaction, that prescribes ingroup favouritism in a new and uncertain group situation.

The second study used a minimal group setting and assessed allocation behaviour as well as attitudes. Allocation matrices were used to assess allocation behaviour within groups and between groups.

Each participant was given a set of six matrices in three conditions in which they could choose how to divide points between the ingroup and the outgroup. In the first condition, participants were requested to allocate points as they wished. The second condition requested participants to allocate points under self-enhancement instructions, and the third condition requested participants to allocate points under self-depreciation instructions (Iacoviello & Spears, 2018).

The results of this second study indicate that individuals perceive ingroup favouritism to be the appropriate strategy when dividing points between the ingroup and the outgroup. This finding was true of both the perceptions towards the ingroup norm as well as biased allocation behaviour that benefitted the ingroup.

In conclusion, a wealth of research demonstrates that ingroup favouritism has been found to be a robust phenomenon in social exchange when individuals are aware of their group membership. It has been argued by (Tajfel, 1970) that individuals have learnt through prior interaction in group settings that ingroup favouritism is the expected strategy, and thus a generic norm in which individuals infer onto new and uncertain groups. This theory has found support through recent research (Iacoviello & Spears, 2018).

Proximity

Proximity can be simply defined as the geographical distance between two or more individuals. There exists empirical evidence to support the theory that the closer players are to each other, the more favourably they are expected to act towards each other.

The study conducted by Huang, Shen, and Contractor (2013), is current research that aimed to assess the effects of spatial proximity, temporal proximity and homophily on collaborations with other players within a large online gaming network.

The online game the researchers chose to focus their study on is EverQuest II. This is a large online gaming network with a population exceeding one hundred thousand players. EverQuest II is set up under a network of smaller servers that each host a population of players. Movement of individuals between servers is discouraged by implementing a financial fee. This results in fairly stable populations under each server. The described study selected a single server named GUK as a sample for the study.

EverQuest II allows players to select groups and work collectively in order to achieve game objectives. In addition to this, the game allows players to partner with one other player to form a dyad in which they earn points in the game. The dependent variable in this study is the formation of a dyadic partnership with the criteria of two or more game objectives being achieved in the partnership.

Players, when registering their memberships, are requested to give certain demographic data such as their address, zip code, gender and age. The independent variable geographic proximity, is calculated from the zip codes and were categorized as either being of the same zip code, short distance (less than 50km), medium distance (50-800km) or long distance (more than 800km).

The results indicate that geographic distance between players has a large and positive impact on forming collaborative ties with other players. Players within close physical proximity to each other had a significantly higher chance of forming partnerships than with those that were further away. An odds ratio shows that players that were within the same zip code of each other were 721 times more likely to enter into partnerships than those that were more than 50km apart. Players within

50km of each other were 21.5 times more likely to enter into partnerships than with those that were more than 50km apart. The relationship between partnership formation and proximity did not have a linear decline with a decrease in proximity. The medium distance of 50-800km had only 20% more impact on collaboration than the long-distance category of more than 800km.

This study has been beneficial in demonstrating that geographic proximity has a powerful effect on collaboration with others. The emergence of cooperation in this study is expected to have arisen due to the potential for face to face interaction between players within the same city (Huang et al., 2013). With an increase in proximity, the challenges for face to face interaction grew dramatically.

Huang et al. (2013), operationalised proximity as geographical or spatial distance. This could be thought of as the most basic understanding of proximity in a social setting (Kiesler & Cummings, 2002).

It is assumed that the closer players are to each other, the more favourably they are expected to act towards each other. The advent of effective telecommunications and virtual environments has, however, forced a shift in the traditional conception of proximity in social functioning. The paradox of being physically distant from others but “feeling close” has become important to investigate, as the traditional importance of spatial distance has become less important with new technologies. Recent discussion around the issue of proximity and social exchange has highlighted the requirement to account for perceived proximity (Wilson, Boyer O'Leary, Metiu, & Jett, 2008).

As Wilson et al. (2008) argues, there are two core features that mediate the effect of perceived proximity. The first of these being communication; the intensity, depth, frequency and personal relatedness of the communication can all lead to increased perceived proximity. The second element that is important is identification. Wilson et al. (2008) uses identification to describe individuals identifying with shared traits that foster an increase in perceived proximity. For example, two females in an office of males may identify with each other’s femininity and ‘feel closer’ to each other. This process is fundamentally a social categorisation whereby individuals identify with an ingroup and consequentially perceive themselves to be closer to their fellow group members.

Exploring the idea of perceived proximity is however outside of the scope of the current study, and due to the fact that focus is kept to the interaction between multiple exchange rules, the current study will limit its attention to geographical proximity.

Self-interest

Self-interest can be defined as an action that only benefits the person involved. An easy example would be an individual that steals from the cash register, the action is goal oriented in that it will have a financial reward and it only benefits the thief. If the intention is to benefit more than the original actor, one could question if the action is purely self-centred or whether it has been influenced by other factors (Cropanzano, Goldman, & Folger, 2005).

Self-interest can also be thought of as rationality whereby individuals make the most rational, profit maximising decision available to them. Rationality has often been assumed by economists as the dominant rule of exchange. The term homo-economicus has been used to describe the type of person that would seek to increase their particular utility at the expense of others (Yamagishi, Li, Takagishi, Matsumoto, & Kiyonari, 2014).

Yamagishi et al. (2014) sought to identify individuals that met the behavioural traits of homo-economicus using the prisoner's dilemma game as well as the dictator game. The games were played on computers and each participant was assured of anonymity. In the prisoner's dilemma game, the participant was given a certain amount of money and they were tasked with the choice of whether to keep the entire endowment or to give it to their partner. This type of prisoner's dilemma game is known as a binary prisoner's dilemma. Participants were randomly assigned after each trial and each participant played three trials of the game. Participants had to decide whether they would give away their money or keep it based on the assumption that the first player had chosen to cooperate or defect. In order to accurately define participants with the behaviour of homo-economicus, the researchers used the choices that participants made when they assumed that the partners had cooperated. It is argued that strong motivations for reciprocation would be evident in the situation, but it is further argued that someone who fits the profile of homo-economicus would not be affected by the motivation to reciprocate. An individual that is purely driven by self-interest would show no concern for fairness norms. The results of this experiment suggested that only a few participants kept their entire endowments. Only 16 percent of people kept their endowments consistently without sharing.

The next game used in the research was the dictator game. Participants all played a one-shot dictator game, and then for the second trial, half of them were randomly assigned to recipients. The participants playing the role of dictator were allowed to choose between eleven amounts varying between zero and 1000 Yen and were then tasked to give their chosen amount to their partner. All participants were then asked to play six more games and they were assigned a different partner for each round. In these six rounds, participants chose a portion of the entire endowment to give. The portions were precalculated and ranged from 0-100% in ten percent increments. The results of this game showed that 15% of participants kept the entire endowment consistently.

The result of this research showed that seven percent of participants, that is 31 out of 446, accurately fit the description of homo-economicus. These participants consistently acted in a way that maximised their own economic profit at the detriment of others. These participants acted consistently in both the prisoner's dilemma and the dictator game. While this research does not show a large portion of people that act in a purely self-centred manner, it does indicate that some people naturally pursue self-centred outcomes. The research did however highlight 28% of participants who consistently cooperated and gave an average of 50% of their initial amounts (Yamagishi et al., 2014).

The research led by Yamagishi et al. (2014), sought to identify people that fitted the homo-economicus psychological profile. The term homo-economicus has often been used in a derogatory manner towards classical economists and has not been taken seriously by social researchers. While very few people fit the profile of homo-economicus, one cannot deny their existence.

Critique of the study would include the fact that fairness and self-interest were studied in isolation. Self-interest can be an ideological trait of an individual but it can also be argued to be norm-induced behaviour, and this means that it can be strengthened or diminished in particular interactive contexts.

The case for self-interest as a norm is also warranted, as argued by Miller (2001). Individuals may pursue self-interest when others around them begin acting in a self-centred manner. Miller (2001) argues that people in a competitive situation may easily begin to act selfishly in fear that they may be exploited by others. The consequences of this is that evidence of self-interest behaviour in experiments can often be confused with motive. A focus of norms emerging through interaction could explain the sometimes-conflicting evidence gained in experiments.

Fairness

Fairness can be thought of as behaviour that is non-discriminatory and in opposition to self-interest. The particular type of fairness that is of focus in the current study can be accurately thought of as inequity aversion. Inequity aversion, as described by Bolton and Ockenfels (2000), as well as Fehr and Schmidt (1999), can be thought of as players seeking equitable outcomes by showing kind acts towards agents that are poor. It is kindness towards the ‘underdog’ as opposed to a purely self-interest-based motivation behind giving that is of interest. This form of fairness is predominant when agents are desiring equitable outcomes.

Fairness thought of as inequity aversion can be distinguished from reciprocity in that it is outcome orientated and is solely focussed on the wealth of each agent and the maintenance of equitable outcomes (Falk & Fischbacher, 2006). Reciprocity, on the other hand, is more focussed on evaluating an action in isolation and rewarding or punishing that particular action based on its outcome and motives (Falk & Fischbacher, 2006).

The study led by Fehr and Schmidt (1999), had the sole aim of modelling fairness as inequity aversion in order to explore and hopefully explain the sometimes-confusing behaviour in social exchange that goes against the standard self-interest model. As argued by Fehr and Schmidt (1999), the definition of an agent who is inequity-averse is an individual who dislikes inequitable outcomes. The consequence of this definition is that the question is raised of how individuals judge outcomes as equitable or inequitable. It has been argued that relative payoffs and the social comparison processes of individuals comparing their payoffs to others is important in judging the equality or lack thereof (Bolton & Ockenfels, 2000; Fehr & Schmidt, 1999).

The model developed by Fehr and Schmidt (1999), assumes the reference group upon which participants make social comparisons to be the other players in the experiment, and the equitable outcome to be determined by the pecuniary outcome of other agents.

In the model, it was assumed that some participants were purely selfish and others displayed aversion to inequitable outcomes. Players were assumed to feel inequity if they were both worse off in monetary terms, as well as if they were better off than other players. Players were also assumed to be more affected by inequity if they were worse off than other players than if they were better off. Utility loss is measured in either the occurrence of advantageous or disadvantageous inequality. An individual will suffer more or lose more utility when the particular inequality is disadvantageous.

Fehr and Schmidt (1999) applied their model successfully to the ultimatum game and the market game; these will be discussed below.

The ultimatum game is a simple game where two players, a proposer and a responder, are required to split a payoff. The proposer is endowed with an amount of money and is required to split the amount with the responder. The proposer can suggest any split to the responder. The responder then has two available strategies; to accept or to reject the offer. If the responder accepts, the split is then performed as originally proposed, however, if the responder chooses to reject, then both proposer and responder receive zero. The ultimatum game has been demonstrated in many experimental settings and robust facts have emerged from these studies (Fehr & Schmidt, 1999). There are rarely proposer offers over 50% and equally rare are any offers below 20% with the majority of offers falling in the 40-50% range (Fehr & Schmidt, 1999). This means that proposers are mostly operating fairly. While proposers do seek profit maximisation, they are constrained by the responder’s ability to reject the offer which would lead to a loss from both parties.

The market game with competition allows a similar format to the ultimatum game, in that there is a single proposer, yet it differs in that there is more than one responder. The responders are in a competitive setting. This is a simple game that works as follows; a proposer will make an offer, and the responders will be faced with a choice of whether or not to accept the offer. If all responders reject the offer, they will all receive nothing. If a few responders accept the offer, a random draw will select one of the accepting responders to receive the payoff. The major finding under these conditions are that responders will accept very low offers, far lower than has been demonstrated by the ultimatum game. Inequality is assumed in this game, and as a consequence, participants have a great motivation to compete for any available resources. Inequity adverse participants are likely to attempt to grab anything available and turn the inequality into an advantageous form for themselves (Fehr & Schmidt, 1999). This finding demonstrates that competition quickly becomes dominant over any fairness norms if there is no way of punishing the wealthy proposer.

The research conducted by Fehr and Schmidt (1999) has been valuable in explaining the evidence that is often in disagreement with the standard self-interest model. The research has demonstrated that fairness and cooperation are evident in the ultimatum game and that the inequity averse model better predicts behaviour than self-interest. It has also been demonstrated that although fairness norms exist, they are relatively weak when competition is included in the design. As demonstrated in the market game, a single player is unable to enforce equitable outcomes (Fehr & Schmidt, 1999).

Fehr and Schmidt (1999) laid an important foundation of fairness being a contributing factor in the decision making of people allocating resources to others. Inequity aversion has been highlighted as the mechanism behind behaviour that contradicts the assumed self-interest model.

In line with the hypothesis of people supporting the underdog, recent research by Schwaninger, Neuhofer, and Kittel (2018) aimed to investigate other-regarding behaviour in exchange networks with disadvantaged individuals.

Most research aimed at negotiated exchange have used dyadic networks that were unable to assess how individual social value orientation would affect giving behaviour to an individual with less structural power i.e. the underdog. The research by Schwaninger et al. (2018) sought to expand on the usual dyadic exchange experiments by adding a third member that had limited structural power in the negotiation.

Two network conditions were used; the first being a triangular three node network which allowed equal communication between nodes, the second being a three-line network which allowed a central node to be connected to both nodes, who in turn were not connected to each other. These two different networks introduced different power structures. In the triangular network, power remained equal among nodes. The three-line network, however, introduced a strong power structure with the central node having a distinct structural advantage over the other nodes.

Two further conditions were introduced which were inclusive treatment and exclusive treatment. Inclusive treatment allowed the third member, the ability to receive a portion of the payoff but was unable to enter into the negotiation. The exclusive treatment did not afford the third member the ability to receive a portion of the payoff.

The inclusive network created an outlier and a potential underdog, as negotiations could only occur between two individuals at a time. This condition then provided the ability to measure fairness as the dyad that entered into negotiation had no obligation to offer any of the payoff to the third member.

The experiment began with the measurement of the social value orientations for each participant. Social value orientation refers to an individual's propensity towards being self-interested (proself) or equitable (prosocial) (Schwaninger et al., 2018).The rest of the experiment was laboratory based with all exchanges and communication being conducted though a computer interface. A series of exchanges were made under all conditions with a computerised random assignment of participants across conditions.

In the inclusive treatment, a dyad decided on an outcome for all three members in the network. In the triangle condition, agreeing pairs kept an average of 11 points each for themselves. The portion of payoff to the third member is of theoretical interest to the study and was classified into three cases of social value orientations of the agreeing pairs. The first combination were two individuals that were prosocial, this pair gave an average of 4 points to the third member. The second combination included one prosocial and the other being proself, this combination gave an average of 2 points to the third member. The third combination were two individuals that were proself, this pair gave an average of 1.1 points to the third member.

The main finding of the study was that on average, dyads that agreed on distributions gave an average of ten percent to the excluded third member. It has been demonstrated that individual social value orientations play a role in the fairness of distributions of resources in an exchange network. These results show conclusive instances of inequity aversion in contradiction to the expected finding of no payoffs under the general assumption of self-interest (Schwaninger et al., 2018).

Studying multilevel-emergence in the social sciences

Thus far, the review has covered social exchange theory and its potential for explaining exchange behaviour. The particular gaps in the literature were then covered with specific focus on exchange rules. Following that, recent empirical support for the set of proposed exchange rules have been discussed. The following section has been devoted to the methodological difficulties in studying exchange behaviour and the macrosocial phenomena that emerge through interaction. Agent-based modelling is argued to be a highly effective research tool that will allow the direct study of the exchange process from microsocial exchange between individuals to the resulting emergent phenomena that results from repeated interaction.

Traditional social psychological research often focuses on macrosocial norms and systems that shape individual behaviour from the top down (Macy & Willer, 2002). There is great merit in this research as it has provided a theoretical base for many phenomena. A good example of top down research would be an experimental setting where a researcher measures the effect of an experimental condition on the individual participants. In this case, the emerged construct is measured, however the dynamic process by which it emerged is not assessed.

Studying emergence from the bottom up has been studied in qualitative research, but until now has been difficult to study in quantitative research designs. This is due mainly to the lack of suitable research methods that are capable of directly studying emergence as a dynamic, temporal process (Kozlowski, Chao, Grand, Braun, &

Kuljanin, 2013). With the use of agent based computational models, researchers are able to endow virtual agents with a set of simple rules that will facilitate the simulation of complex social systems. The ability to demonstrate that a certain rule or combination of rules leads to emergent phenomena is the core objective of bottom up research using an agent-based model (Kozlowski et al., 2013). This bottom up approach allows researchers not only to measure the emerged construct, but also to focus specifically on the process and mechanisms of the emerging construct (Kozlowski et al., 2013).

The following section has been devoted to describing agent-based modelling with examples of agent-based modelling being provided relating to their value as a research method for testing theory.

Agent based simulations

Agent based models are basic simulations of social interaction run through a computer interface. Agent based models are not confined to social life, they have been used to model traffic flow in cities (Chen & Zhan, 2008), pedestrian movements (Kerridge, Hine, & Wigan, 2001), avian flock patterns (Reynolds, 1987) and cell behaviour (Pogson, Smallwood, Qwarnstrom, & Holcombe, 2006) as a few examples. An agent-based model uses precise mathematical rules that guide an agent's interaction with other agents. Due to the fact that there are none of the usual constraints attributed to sampling human participants, researchers are able to run an infinite number of replications with varying rules. Researchers can also include as many agents as they wish. The only constraint is the computing power available to the researcher.

Applications such as Netlogo have simplified the task of building agent-based models which has, in turn, opened up the research method to many researchers. The first step in building a model is to develop rules that the agents will use in their interaction. The most commonly supported stance with developing rules is to keep it as simple as possible. The phrase "keep it simple, stupid" is often referenced when deciding on model parameters. The basic idea is to use as few simple rules as possible, and to slowly add rules or adapt them to create the emergent phenomenon.

The most obvious benefit to keeping it as simple as possible is that it reduces the complexity in developing the model. More importantly though, complex macrosocial phenomena do not necessarily stem from complex cognition in individuals. As argued by Macy and Willer (2002), humans follow simple heuristics, norms, social habits and moral codes. These, in a sense, are simple rules that often lead to highly complex emergent patterns in real life.

In order to accurately simulate an emerged phenomenon, it is important to be sure that chosen rules are sufficient to produce the outcome that is observed empirically. Epstein (1999) discussed the issue of generative sufficiency where a set of rules need to be sufficient in reproducing the macrophenomenon even if replicated a number of times. Attention need also be focussed to the fact that even if a rule or a particular combination of rules leads to the emergence of an observed phenomenon equivalent to what is empirically observed, it does not necessarily mean that these are the rules that are at play. They are simply candidates which require further investigation. The method of comparing the generated macro-structure to that of human data with the use of inferential statistics proves generative sufficiency of the rules underlying the agent-based model (Epstein, 1999).

A illustrative example of a study that used simple rules to generate an emergent phenomenon was the study led by Reynolds (1987) that aimed to replicate the flocking behaviour of birds in flight. The three rules used to direct the autonomous agents were simple:

- Agents should not occupy the same space as another agent or foreign object. This was to avoid collisions with other agents.
- Agents should move at the same speed as each other as well as travel in the same direction.
- Agents should be cohesive and attempt to remain close while not intruding on the personal space of other agents. Each agent would desire to be centred, yet is constrained by the rule of collision avoidance.

Agents where then placed across a grid. Immediately, agents followed the centring rule and all converged to one area. The group avoided collisions with each other so all agents occupied their own space with relatively even spaces around each agent.

The group quickly became polarized following the same direction and speed as each other (Reynolds, 1987).

This study is a powerful example of how agent-based modelling can uncover the simple rules that lead to emergent phenomenon. An important demonstration is that agents are modelled as autonomous beings that do not rely on a centralised authority to guide interaction. As Macy and Willer (2002) have clearly pointed out, neither the flock nor individual birds were modelled, the focus was to model their interaction with each other.

It is important to note however, that just because a set of rules have led to a particular emerged phenomenon, does not mean that there are no other rules or explanations for the emergence. The decision of which particular parameters (rules) that need to be manipulated should be driven by theory. Agent based modelling is a powerful tool for exploring microsocial interactions and their resulting emerged phenomena, but without theoretical grounding, the results would be meaningless. In order to maintain a culture of good science, researchers must use theoretical and empirically proven parameters (Macy & Willer, 2002).

Using theory driven parameters in an agent-based model affords researchers with another powerful advantage, and that is the ability to test theoretical assumptions behind emergence. A good example of modelling being used to test theory is the early study on attractiveness and couple formation by Kalick and Hamilton (1986).

It was long theorised that potential mates were chosen based on how well they matched their own attractiveness level, this was known as the matching hypothesis (Kalick & Hamilton, 1986). Evidence in studies that focussed on this area soon failed to support this view, and it was argued that people tend to choose the most attractive partner possible (Walster, 1970; Walster, Aronson, Abrahams, & Rottman, 1966).

Kalick and Hamilton (1986) devised an agent-based model in order to study the agent level goals of couple formation. A simple model was created where three simulations were run testing the two argued mechanisms for mate selection. In the first simulation, the rule was set for agents to select partners based on the highest possible attractiveness score. The second simulation used a rule where agents would choose the best matching partner to their own attractiveness score and the third simulation relied on a combination of matching and finding the most attractive mate.

The model was a simple rule-based procedure and is detailed below. Two thousand agents were created with 1000 being male and 1000 being female. Each agent was then assigned an attractiveness score ranging between 1 and 10. Both attributes of gender and attractiveness were permanently affixed to each agent for the duration of the simulation. Agents were then randomly paired for a date and they were then faced with a decision of whether to accept or reject their partner. The decision was made based on the attractiveness of the partner in relation to the agents own attractiveness. In order for the couple to be successful, both agents had to make the decision to accept their partner. Once a successful couple had been formed, they were removed from the dating pool.

The results showed that when agents were given the rule of finding the most attractive partner, an intercouple correlation of .55 was found which matches what has been empirically observed. The simulations that included matching combined with an attractiveness rule had correlations that exceeded what has been empirically observed (Kalick & Hamilton, 1986). An explanation for this is that highly attractive couples tend to form early in the experiment and are then removed from the dating pool. With an increase in time, the attractiveness of the remaining agents drops along with the attractiveness of the resulting couples (Smith & Conrey, 2007). The authors argue that the results must be cautiously interpreted as measurement error in past empirical research was evident whereas in the models, this factor was absent. In addition to this, the simulation with the rule of seeking the most attractive partner led to an increase in intracouple correlation over time. Kalick and Hamilton (1986) argue that this trend supports findings that casual couples are weakly correlated in this regard, with more serious couples being more highly correlated. The results of this simulation suggest that attractiveness seeking is more important than the favoured matching hypothesis (Kalick & Hamilton, 1986)

The use of agent-based modelling for simulating macrosocial structures from agent level interaction is well demonstrated, yet the process of comparing these simulations to real life data has yet to be done effectively. Typically, agent-based models have been qualitatively compared to empirical data which leaves the researcher with the responsibility to ensure that simulated outcomes sufficiently resemble real life behaviour (Silverman, 2018). Consequently, this places great constraints on the usefulness of simulations to explain real life behaviour. If one's wish was to specify the rules that lead to birds flocking, in a culture of good science, we would need to quantitatively validate the results instead of making a subjective judgement of whether or not the results simply look like flocking behaviour.

In the current study, the aim has been to tease apart and study the relative importance of multiple exchange rules in different contexts. In order to validate the simulated results of this study, a quantitative metric was required. A laboratory-based study of social exchange was used in order to quantitatively compare the outcomes of the simulation to actual human exchange decisions. The method of comparison was achieved automatically by uploading empirical data into the simulator with an output data file that specified the comparison between the empirical data to that of actual human exchange decisions.

Chapter 3: Methodology

Research design

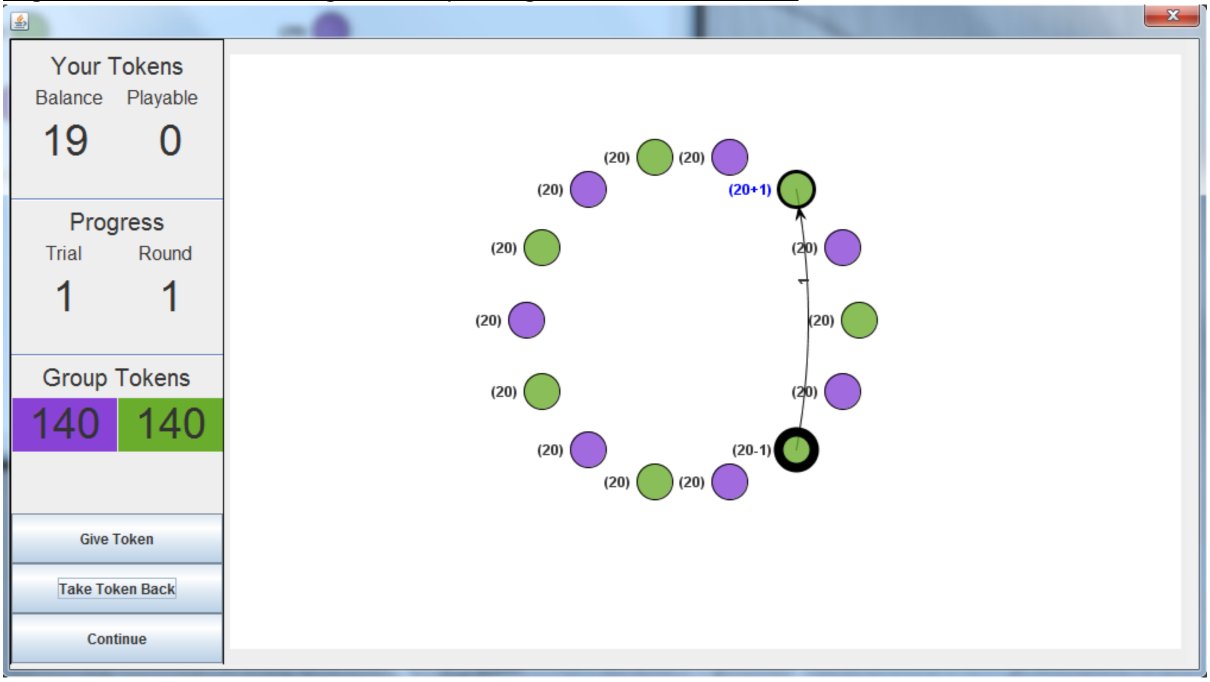
Section 1: Virtual Interactive Application (VIAPPL) research design

In the current study, an agent-based model was used to replicate the bottom up emerged behavioural patterns observed in the human VIAPPL experiments. The VIAPPL studies have been outlined below, following this, the agent-based model has been described.

The VIAPPL study by Durrheim, Quayle, Tredoux, Titlestad, and Tooke (2016) was developed to study social exchange behaviour within an interacting exchange network over time. The study used an experimental setting where participants were stationed at computers with no face to face interaction. The participants were allocated a number of tokens at the start of the game and were instructed to allocate a token every round to either one of the fourteen players. The experiment was run over forty rounds with the recorded decision of each participant's allocation to either themselves or to another specific person within the network. Figure 1 graphically represents the interface that participants used to interact with one another. The following information was available on each players screen; the players wealth, the wealth of each participant within the network, the accumulative wealth of each group and the progress of the game indicated by the round number.

In order to test how network structure and existing norms influence exchange behaviour, two experimental conditions were introduced. The first condition was the minimal group situation which introduced visible group identity and the second condition was wealth inequality. These two conditions both had a corresponding control condition where no manipulation of group identity or inequality of wealth was introduced. These four conditions were fully crossed in a factorial design and four replications were run for each condition. Table 1 illustrates the VIAAPL design with the number of replications per condition. The two experimental conditions, visible group identity and inequality, have been described in more detail below.

Figure 1: The VIAPPL game depicting a token allocation



Note. This figure depicts the interface from the perspective of the 6th player as denoted by the bold black outline of the 6th avatar. The arrow indicates the decision of the 6th player to allocate a token to the 2nd player. The experimental condition depicted here is an equal status group condition.

Table 1: Replication table for the human games

	Equality	Inequality
Group condition	4	4
Individual condition	4	4

The group condition was introduced by randomly assigning participants into two groups. Participants were not aware of the random assignment and were told that they were assigned to particular groups based on their choice in a categorization task. Participants were requested to choose between two paintings, one having been painted by Klee and the other by Kandinsky, and were placed into the respective groups. The participants were aware of their group membership by the colour of their avatar on the play screen. A set of experiments were also run with an individual condition in which players were not aware of their group membership. In the individual condition, participants were not aware of their group membership as all 14 players had the same colour avatars.

An inequality condition was introduced where participants were given unequal starting token balances. In the group and individual conditions under inequality, there existed a high and low status group with one of the groups having been allocated 30 tokens while the other was given 10. In the group and individual conditions under equality, each participant was allocated 20 tokens.

These two conditions were introduced in order to study the effects that different contexts have on exchange behaviour. The data from these human games were collected in 2014 by the Department of Psychology on the University of KwaZulu-Natal Pietermaritzburg campus.

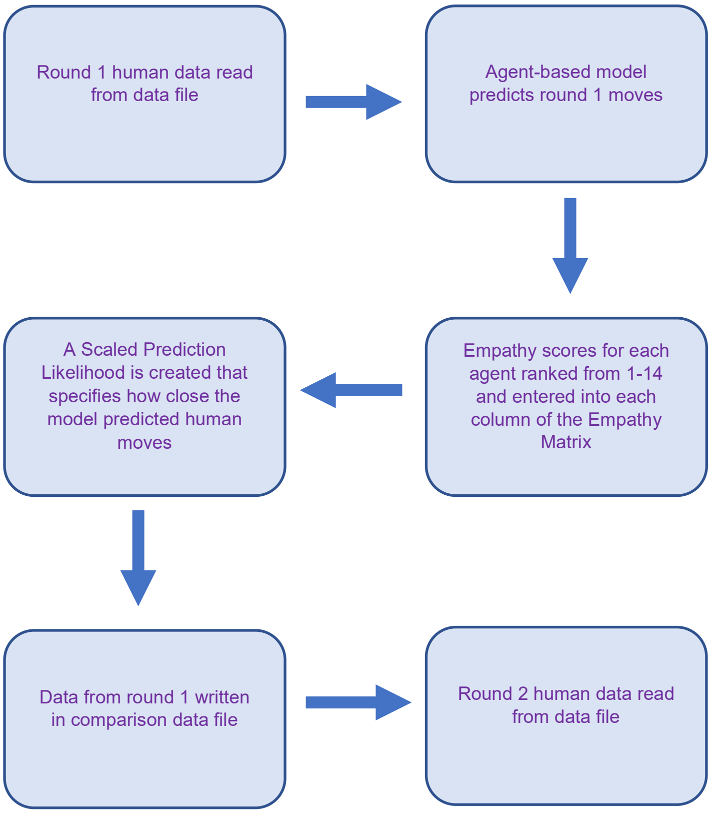
Section 2: Game simulator

An agent-based model was developed to uncover the agent level decision making that led to the emerged results obtained in the VIAPPL data.

The simulator used in this research has been programmed in Netlogo (Wilensky, 1999). Netlogo is a popular interface used for modelling complex interaction over time (Tisue & Wilensky, 2004). It is praised for its simplicity which affords beginning modellers the ability to program simple models in order to research human behaviour. Netlogo was chosen for the fact that it was a simple environment in which to program the simulation and that it is able to accept data input in the form of a .csv file.

The simulator is designed in such a way that it is fed with a single row of data at a time, sequencing throughout the entire game. The simulator reads a row of data, representing the starting conditions for round 1. It then simulates play based on the starting conditions and the game rules defined by the sliders. It then reads the starting conditions for round 2 of the human game and continues this process until it reaches 40 rounds. A data file is automatically created in the beginning of the simulation with the data from each round written as the simulator progresses throughout the 40 rounds. Each row of data details the results of the simulated round alongside a comparison with the human round. It was then possible to compare the outcomes of human and simulated play after each round. Figure 2 graphically represents the comparison process between the human games and the simulated output.

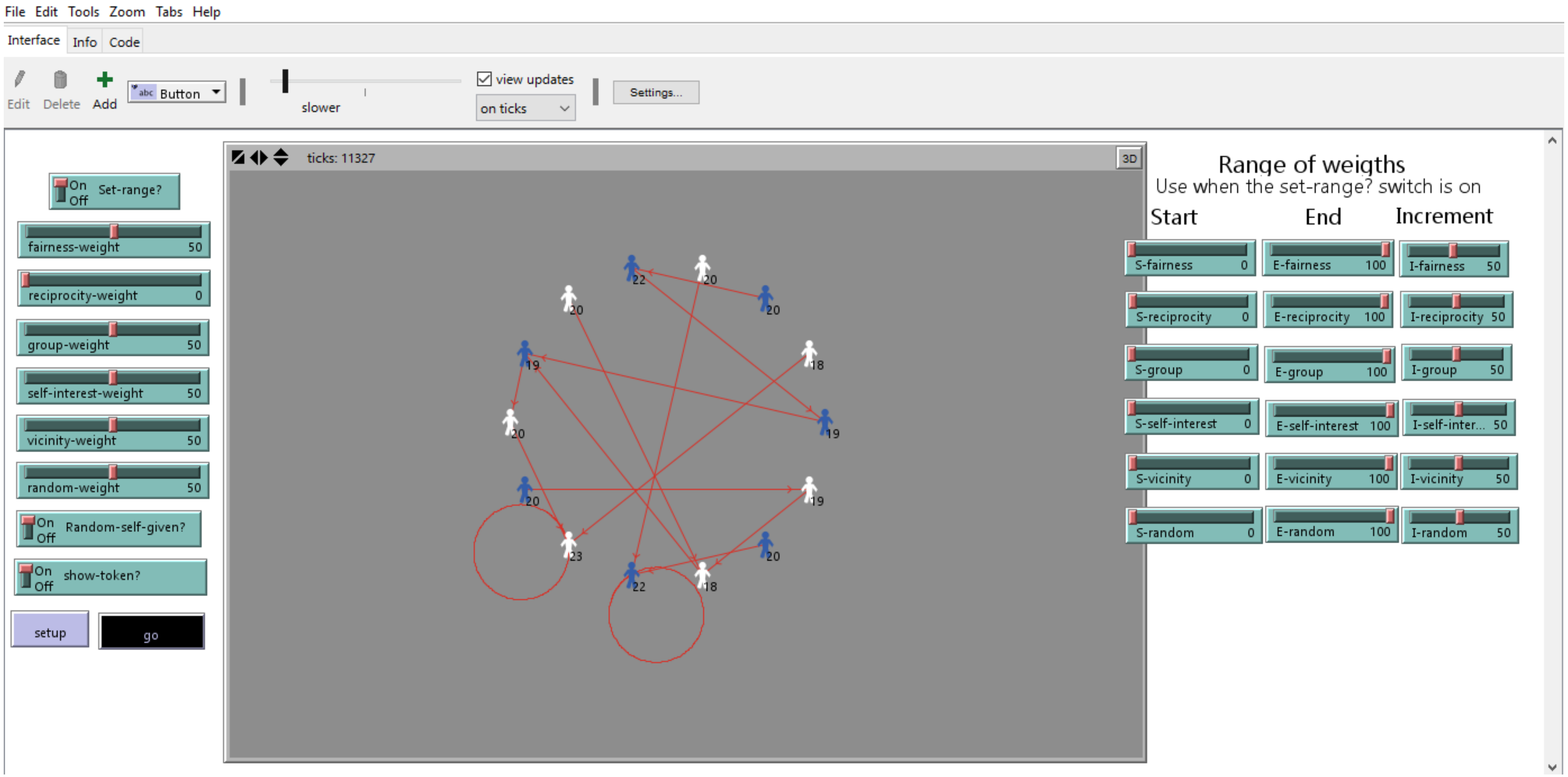
Figure 2: Simulator comparison procedure



The simulator, like the human game, is set up with fourteen virtual agents and is graphically represented in a circular format (See the comparison between the VIAPPL game (Figure 1) and the game simulator (Figure 3)). The representation will change based on whether the simulation includes a group condition or individual condition. In the group condition, agents have been coloured blue and white in an alternate order. In the individual condition, all agents are coloured white. Token allocations are represented graphically as arrows between agents and as a circle in the event of self-allocation.

The independent variables namely, vicinity, fairness, reciprocity, self-interest, random and ingroup favouritism are manipulated using a set of sliders that range from zero to one hundred. Using one particular combination of the six independent variables will result in one game of forty rounds. The simulator has also been programmed to be able to run multiple combinations of the independent variables in one simulation. This is executed by setting a range for each variable between zero and one hundred and then specifying the increments to which each variable should increase after each game.

Figure 3: Screenshot of the game simulator



The token exchanges are depicted as the red lines between human figures, an arrow gives indication of the direction of giving. The circles represent instances of self-giving. The numbers next to the agents represent the wealth in the number of available tokens for each corresponding agent. To the left of the image, a set of sliders are designed to set the weightings for each factor. These sliders are automatically controlled when the range sliders (to the right of the image) are used. The 'Range of weights' function sets the minimum weighting for each factor as well as the maximum weight. The increment sliders control the increments of increase in weightings for each round. The simulation as depicted here is set up to simulate every combination of all 6 factors at 3 levels of 0, 50 and 100.

Model of social exchange

In the development of the agent-based model, it was necessary to formulate a mathematical model in order to model exchange in the VIAPPL setting. The model was developed in a collaboration with the school of psychology and the school of mathematics, statistics and computer science of the University of Kwazulu-Natal (Durrheim et al., 2013).

In order to model exchange behaviour, a single matrix for each modelled behavioural construct was used. These matrices were summed to form a final matrix termed the Empathy Matrix. The Empathy Matrix was a 14 x 14 matrix that represented the computed likelihood that each agent would give their token to each of the 14 agents in the game. The simulator depicted in Figure 3 used the highest likelihood to make the eventual allocation decision. It was necessary to calculate wealth in each round and the change in wealth at the end of each round, two vectors were used to accomplish this. The notation and vectors have been described below, following that, the matrix calculations have been explained (unless stated otherwise, all matrix calculations have been demonstrated with $N = 4$).

The participants modelled as agents are labelled $p_1, p_2, p_3, p_4 \ldots \ldots, p_N$. In the current study, both the human games and simulations: $N = 14$.

The wealth of the participants in the beginning of each round (r) is defined by the vector;

$$W^{(r)} \coloneqq \{w_1, w_2, w_3, w_4, \ldots \ldots \ldots, w_N\}$$

Where w_i is the wealth of participant p_i for $i \in [1 - N]$.

A vector to calculate the change in the wealth of each participant is defined as;

$$C^{(r)} \coloneqq \{c_1, c_2, c_3, c_4, \ldots \ldots \ldots, c_N\}$$

Where c_i is the change in wealth of participant p_i for $i \in [1 - N]$.

Each change in wealth, c_i can be a value in the range -1 (in the case that participant p_i gave his token away and received no token) and $N - 1$ (in the case that there was self-giving as well as every other participant allocating their token to participant p_i). One exception is the situation where a player has spent all their tokens and so has none to give away. In this case, the numeral would be set to zero. In the case where $N = 4$, we could assume an example where, $W^{(5)} := \{10, 16, 0,14\}$. If p_1 gave their token to p_3, p_2 gave to p_1, p_4 gave to p_3 and p_3 self-gave; the change vector for the end of round 6 would be $C^{(6)} := \{0, -1, 2, -1\}$. The wealth vector for beginning of the next round would then change to $W^{(7)} := \{10, 15, 2,13\}$.

Empathy Matrix

The Empathy Matrix developed by Durrheim et al. (2013) is a tool for summarizing the decision rules that form the behaviour of the simulated agents. The matrix, in an $N \times N$ form, determines the likelihood that each participant would receive a token from every participant, including themselves (in the main diagonal) in each round.

The Empathy Matrix is formulated by the matrix sum of six different matrices, namely the Fairness Matrix, Reciprocity Matrix, Ingroup favouritism Matrix, Self-interest Matrix, Vicinity Matrix and Random Matrix. Each of these matrices represent an exchange rule.

- The Fairness Matrix allows the operationalisation of the exchange rule to allocate a token to the poorest participant.
- The Reciprocity Matrix allows the operationalisation of the exchange rule to reciprocate a token that was given in the previous round.
- The Ingroup favouritism Matrix allows the operationalisation of the exchange rule to give a token to favour the ingroup.
- The Self-interest Matrix allows the operationalisation of the exchange rule to give a token to oneself.
- The Vicinity Matrix allows the operationalisation of the exchange rule to favour one’s neighbours when deciding on who to give a token to.

- The Random Matrix allows the operationalisation of uncertainty in human decision making.

Each of these matrices have N rows and N columns, where N is the number of participants. In the Empathy Matrix, the columns specify the givers while the rows specify the receivers. Thus, for each particular column, there are N possible receivers (the giver inclusive) if self-giving is allowed; otherwise there are $N-1$ possible receivers (i.e. excluding the giver). Each time a token is given, a possible receiver with the largest value in a column will receive the token. Each participant gives a token per round to either themselves or to another participant. The Empathy Matrix is recalculated at the beginning of each round.

In order to illustrate the mechanics of the Empathy Matrix, a simple example is given below;

$$E^{(r)} = \begin{pmatrix} E_{1,1} & E_{1,2} & \dots & E_{1,14} \\ E_{2,1} & E_{2,2} & \dots & E_{2,14} \\ \dots & \dots & \dots & \dots \\ E_{14,1} & E_{14,2} & \dots & E_{14,14} \end{pmatrix}$$

In the example matrix E, each entry, $E_{i,j}$, is a value that acts as an intercept between a giver and receiver. A givers perspective would be a particular column with N rows. If the entry, say $E_{1,2}$, were the highest value in column 2, this would mean that p_2 would desire to allocate a token to p_1. Likewise, If the entry, $E_{14,3}$, were the highest value in column 3, then p_3 would desire to allocate a token to p_{14}.

Fairness Matrix

The Fairness Matrix allows the operationalisation of the decision to allocate a token to the poorest participant. The Fairness Matrix is calculated by ranking the participants according to their wealth. A fairness value, say F_{ij}, is assigned to each participant from the poorest to the richest. The value of F_{ij} must be in the range zero and one (i.e. $F_{ij} \in [0, 1]$.). The ranking allows the poorest players to be favoured to receive a token. These fairness values are then entered into the matrix with the assumption that all participants will give the same value to each participant in the game.

The Fairness Matrix is calculated as follows: Rank the participants based on their wealth. A participant with the highest number of tokens is ranked the highest r_h while a participant with the least number of tokens is ranked the lowest r_l . The highest rank is 1 while the lowest possible rank is N. If there are one or more ties in the ranking, then $r_l \leq N$.

Calculate each F_{ij} using the formula r_{ij}/ r_l . Note that $r_{i0} = r_{i1} = \cdots = r_{in} = r_i \quad \forall\, i \in \{0,1, \dots, N\}$

If $N = 4$, and we consider the wealth vector used above, $W^{(5)} := \{10, 16, 0,14\}$, the matrix values would then be entered as follows:

$$F^{(5)} = \begin{pmatrix} 3 & 3 & 3 & 3 \\ 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \\ 2 & 2 & 2 & 2 \end{pmatrix}$$

If there is a tie in the number of tokens that two or more players have, they would be assigned the same fairness value and the values would decrease normally. If the participants were ranked according to the wealth vector of round 5, ($W^{(5)} := \{10, 8, 8,14\}$) the Fairness Matrix values would be entered as follows;

$$F^{(5)} = \begin{pmatrix} 2 & 2 & 2 & 2 \\ 4 & 4 & 4 & 4 \\ 4 & 4 & 4 & 4 \\ 3 & 3 & 3 & 3 \end{pmatrix}$$

The values in the Fairness Matrix have then been normalised to range between 0 and 1. This is achieved by dividing each value by the highest value in the particular column. If the wealth vector $W^{(5)} \coloneqq \{10, 8, 8{,}14\}$ is used, the matrix with normalised values would be entered as follows;

$$F^{(5)} = \begin{pmatrix} 0.5 & 0.5 & 0.5 & 0.5 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 0.75 & 0.75 & 0.75 & 0.75 \end{pmatrix}$$

Reciprocity Matrix

The Reciprocity Matrix is calculated by referring back to the previous round. If p_1 were to give their token to p_4 then, in the following round, it would be assumed that p_4 would feel a desire to reciprocate. If two participants gave a token to p_4 in the previous round, it is assumed that he/she would desire to allocate a token to both players.

A reciprocity value, R_{ij}, is equal to 1 if participant i gave a token to participant j in the previous round, otherwise $R_{ij} = 0$. The Reciprocity Matrix changes after each round.

As an illustration, let us assume that in round 3, p_4 gave their token to p_2, p_1 gave their token to p_3, p_2 gave their token to p_1 and p_3 gave their token to p_1. In the following round, the values in the Reciprocity Matrix are entered as follows;

$$R^{(4)} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

Self-interest Matrix

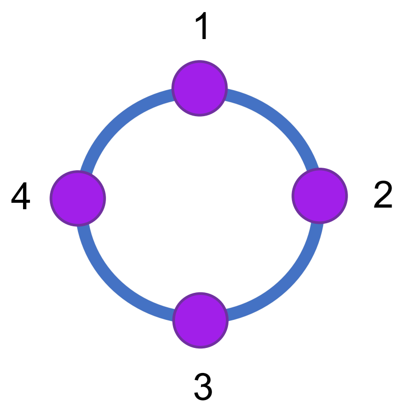
Self-interest is modelled quite simply with the main diagonal having 1's in the entries. The self-interest value, S_{ij}, is equal to 1 if $i = j$, otherwise $S_{ij} = 0$. The Self-interest Matrix remains constant throughout the game.

The Self-interest Matrix is illustrated below;

$$S = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

Vicinity Matrix

The Vicinity Matrix has been explained based on the game situation with $N = 4$. The placement of the participants within the game is graphically represented below.



A vicinity value, V_{ij}, is a reflection of the distance between two participants, i and j.

1) For each participant, the Netlogo function is used to calculate the distance d_{ij} between participant P_i and another participant P_j, where i and j are integers that represent the sequence number of a participant.

2) The distances in (1) are used to form a distance matrix showing the distance from a participant (matrix column) to another participant (matrix row).

   Note that the distance from a participant to itself is zero. Also $d_{ij} = d_{ji}$. In the given game situation of $N = 4$, it should be observed that $d_{1,2} \cong d_{1,4}$. Assume this value to be 1 and $d_{1,3}$ = 2.

$$d = \begin{pmatrix} 0 & 1 & 2 & 1 \\ 1 & 0 & 1 & 2 \\ 2 & 1 & 0 & 1 \\ 1 & 2 & 1 & 0 \end{pmatrix}$$

The values in the distance matrix d are then normalised to obtain V in the range $0 \leq V_{ik} \leq 1$. This is done by dividing the entries in each column by the maximum distance, d, in that column. The value obtained is then subtracted from 1. This is calculated by the formula below.

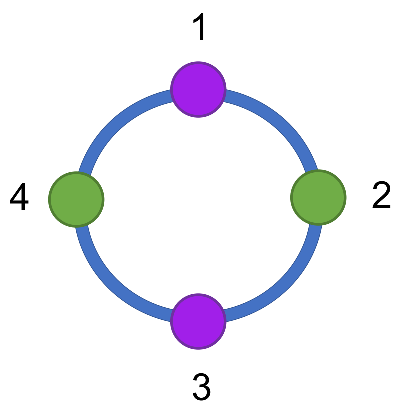
$$V_{ij} = 1 - \frac{d_{ij}}{d_{max}} \ (d_{ij} \neq 0)$$

$$V = \begin{pmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{pmatrix}$$

Note: If $d_{ij} = 1.5$; $V_{ij} = 1 - \left(\frac{1.5}{2}\right) = 0.25$ which implies that the distance $d_{ij} = 1$ is preferred to $d_{ij} = 1.5$. In general, the farther the distance between participants, the less desirable it would be to allocate a token. As the vicinity between players never changes, the matrix remains constant throughout the game.

Ingroup favouritism Matrix

The Ingroup favouritism Matrix has been explained in reference to the game situation where $N = 4$. The colour of the dots in this figure represent each participant's group membership.



A group value, G_{ij}, is equal to 1 if participant i is in the same group with participant j, otherwise $G_{ij} = 0$.

The Ingroup favouritism Matrix, as in the case with the Vicinity Matrix, remains constant throughout the game.

As an illustration, the values of the group matrix for $N = 4$ are entered as follows

$$G = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix}$$

Random Matrix

The Random Matrix uses random entries in order to operationalise uncertainty in human decision making. The Random Matrix is calculated using Netlogo's random-float function. A random value in the range of 0 and 1 is assigned to each row in each column in the matrix with equal probability. The Random Matrix changes at each round of the game.

As an illustration, a Random Matrix for $N = 4$ is shown below;

$$RD^{(4)} = \begin{pmatrix} 0.54 & 0.78 & 0.55 & 0.22 \\ 0.99 & 0.87 & 0.91 & 0.30 \\ 0.50 & 0.73 & 0.10 & 0.8 \\ 0.56 & 0.01 & 0.01 & 0.09 \end{pmatrix}$$

<u>Computing the Empathy Matrix</u>

The sum of the six matrices above are used to create the Empathy Matrix (Durrheim et al., 2013). If we consider round 6 with the wealth vector of $W^{(5)} :=$ $\{10, 16, 0, 14\}$ and when in round 5, p_1 gave a token to p_3, p_3 gave to p_2, p_2 gave to p_1 and p_4 gave to p_2. The Empathy Matrix for round 6 would be calculated as follows;

$$E^{(6)} = F^{(6)} + S + V + RD^{(6)} + G + R^{(6)}$$

$$\begin{pmatrix} 0.75 & 0.75 & 0.75 & 0.75 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 1 & 1 & 1 & 1 \\ 0.5 & 0.5 & 0.5 & 0.5 \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} + \begin{pmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{pmatrix} +$$

$$\begin{pmatrix} 0.54 & 0.78 & 0.55 & 0.22 \\ 0.99 & 0.87 & 0.91 & 0.30 \\ 0.50 & 0.73 & 0.10 & 0.8 \\ 0.56 & 0.01 & 0.01 & 0.09 \end{pmatrix} + \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$E^{(6)} = \begin{pmatrix} \mathbf{3.29} & 2.03 & \mathbf{3.3} & 1.47 \\ 2.74 & 3.12 & 1.66 & 1.55 \\ 2.5 & \mathbf{3.23} & 3.1 & 2.3 \\ 1.56 & 2.51 & 1.01 & \mathbf{2.59} \end{pmatrix}$$

In this example, the agents that received tokens are indicated by the bold entries in the matrix. p_1 self-gave, p_2 gave a token to p_3, p_3 gave a token to p_1 and p_4 self-gave. The change vector for the end of round 6 would then be $C^{(6)} \coloneqq \{1, -1, 0,0\}$. The wealth vector for the end of round 6 (beginning of round 7) would then be $W^{(7)} \coloneqq \{11, 15, 0,14\}$.

In addition to simply adding the six matrices together, each matrix can be weighted in order to increase or decrease the influence that the particular factor has on the Empathy Matrix. The ability to weight each factor in different combinations provides the ability to determine which psychological theory is most important in matching the modelled data to that of the human experiments.

The Empathy Matrix E, is then calculated as below:

$$E_{ij} = fw * F_{ij} + sw * S_{ij} + vw * V_{ij} + \mathrm{rd}w * RD_{ij} + gw * G_{ij} + rw * R_{ij}$$

Where:

fw is the Fairness weight

rw is the Reciprocity weight

gw is the Ingroup Favouritism weight

sw is the Self-interest weight

vw is the Vicinity weight

rdw is the Random weight

In order to illustrate this, the example of the wealth vector for round 5, $W^{(5)} := \{10, 16, 0,14\}$ has been used. In round 5, p_1 gave a token to p_3, p_3 gave to p_2, p_2 gave to p_1 and p_4 gave to p_2. The weights have been set as; $F = 5, S = 5, V = 5, RD = 5, G = 10, R = 10$. The Empathy Matrix would then be calculated as follows;

$$5 \times \begin{pmatrix} 0.75 & 0.75 & 0.75 & 0.75 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 1 & 1 & 1 & 1 \\ 0.5 & 0.5 & 0.5 & 0.5 \end{pmatrix} + 5 \times \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} + 5 \times$$

$$\begin{pmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{pmatrix} + 5 \times \begin{pmatrix} 0.54 & 0.78 & 0.55 & 0.22 \\ 0.99 & 0.87 & 0.91 & 0.30 \\ 0.50 & 0.73 & 0.10 & 0.8 \\ 0.56 & 0.01 & 0.01 & 0.09 \end{pmatrix} + 10 \times \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix} +$$

$$10 \times \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$\begin{pmatrix} 3.75 & 3.75 & 3.75 & 5.75 \\ 2.5 & 2.5 & 2.5 & 2.5 \\ 5 & 5 & 5 & 5 \\ 2.5 & 2.5 & 2.5 & 2.5 \end{pmatrix} + \begin{pmatrix} 5 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 \\ 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 5 \end{pmatrix} + \begin{pmatrix} 0 & 2.5 & 0 & 2.5 \\ 2.5 & 0 & 2.5 & 0 \\ 0 & 2.5 & 0 & 2.5 \\ 2.5 & 0 & 2.5 & 0 \end{pmatrix} +$$

$$\begin{pmatrix} 2.7 & 3.9 & 2.75 & 1.1 \\ 4.95 & 4.35 & 4.55 & 1.5 \\ 2.5 & 3.65 & 0.5 & 4.8 \\ 2.8 & 0.05 & 0.05 & 0.45 \end{pmatrix} + \begin{pmatrix} 10 & 0 & 10 & 0 \\ 0 & 10 & 0 & 10 \\ 10 & 0 & 10 & 0 \\ 0 & 10 & 0 & 10 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 10 & 0 \\ 10 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 \\ 0 & 10 & 0 & 0 \end{pmatrix}$$

$$E^{(6)} = \begin{pmatrix} \mathbf{21.45} & 10.15 & \mathbf{26.5} & 9.35 \\ 19.95 & 21.85 & 9.55 & 14 \\ 17.5 & 21.15 & 20.5 & 12.3 \\ 7.8 & \mathbf{22.55} & 5.05 & \mathbf{17.95} \end{pmatrix}$$

In this example, p_1 self-gave, p_2 gave to p_4, p_3 gave to p_1 and p_4 self-gave. Reflecting back to the wealth vector for round 5, $W^{(5)} := \{10, 16, 0,14\}$, it is noted that although p_3 had the desire to give a token to p_1 they had no available tokens and were unable to give the token to p_1. The change vector at the end of round 6 would be $C^{(6)} := \{0, -1, 0,1\}$. The wealth vector at the end of round 6 (the beginning of round 7) would be updated to $W^{(7)} := \{10, 15, 0,15\}$.

<u>Comparing fit between simulator and human play</u>

<u>Predicted Rank (PR):</u>

The empathy scores for each agent are ranked in each column of the Empathy Matrix to represent the preferred order of allocating tokens. Each rank is a number in the range $[1\!:\!N]$ where N is the number of participants ($N = 14$ in the current study). The number of ranks is equal to the number of unique values and will range between 1 and N if all the values in the Empathy Matrix are unique. An agent ranked 1 is preferred over all other agents. Generally, an agent ranked X is preferred to an agent ranked Y (where $X < Y$). If there are one or more ties between agents, the token is given to the player with the lowest wealth. If they both have the same wealth, a random choice is made.

As an example, the Empathy Matrix for round 6 would be ranked as follows;

This is the Empathy Matrix before ranking.

$$E^{(6)} = \begin{pmatrix} \mathbf{21.45} & 10.15 & \mathbf{26.5} & 9.35 \\ 19.95 & 21.85 & 9.55 & 14 \\ 17.5 & 21.15 & 20.5 & 12.3 \\ 7.8 & \mathbf{22.55} & 5.05 & \mathbf{17.95} \end{pmatrix}$$

This is the same matrix ranked in order of giving preference.

$$E^{(6)} = \begin{pmatrix} 1 & 4 & 1 & 4 \\ 2 & 2 & 3 & 2 \\ 3 & 3 & 2 & 3 \\ 4 & 1 & 4 & 1 \end{pmatrix}$$

These ranks are then compared to the exchanges that occurred in the human experiments and are used to calculate the scaled prediction rank. This comparison is made by comparing the actual allocation made by each of the human agents with the vector of ranks in the output column for the corresponding simulated agent. For example, in $E^{(6)}$ above, if human player 1 (represented as column 1) self-gave, the simulator would have predicted the outcome correctly.

Instead of measuring fit in terms of a binary decision (accurate or inaccurate prediction), scaled prediction ranks were used to estimate the degree of accuracy. A simulated decision would obtain a higher accuracy score if the human agent allocated to player ranked 2 than to player ranked 14.

Scaled Prediction Rank (SPR):

By scaling the predicted rank, a numerical value of how close the model is to a correct prediction can be specified. The scaled prediction rank is a value in the range 0 and 1 inclusive $(0 <= SPR <= 1)$, and is calculated as follows;

$$SPR = \{1 - [\,(PR - 1)\,/\,(N - 1)\,]\,\}$$

Thus, a value of 1 implies that the agent ranked 1 actually received a token in the real game while a value of 0 implies that the agent that received a token was ranked N (the last). The closer an SPR is to 1, the better the prediction. The scaled prediction score for the ranks 1 to 14 are displayed in table 1 below. These vary on a scale from 0 to 1 with a mean of (*M* = 0.5, *SD* = .31). An Average Scaled Prediction rank, calculated as SPR/N, is calculated per round and specifies the prediction accuracy of each round.

Table 2: Scaled prediction ranks

1	1
2	0,923077
3	0,846154
4	0,769231
5	0,692308
6	0,615385
7	0,538462
8	0,461538
9	0,384615
10	0,307692
11	0,230769
12	0,153846
13	0,076923
14	0

Simulator procedure

Data from the human games were fed as a single data set into Netlogo which ran one row at a time through the entire game. A description of the human game has been given followed by a description of the procedure for each simulation. Following this, a description of the comparison data has been laid out.

A total of sixteen human games were used to compare against the simulator (See Table 1 for a graphical representation of replications). There were four experimental conditions with 4 games per condition.

Running the simulations

During the setup of the particular simulation, a dataset from the VIAPPL experiments conducted in 2014 were selected, converted to .csv format and uploaded into Netlogo. Parameters were then set up to define the particular simulation and to match the experimental conditions of the human game. The first step in setup is to define how many tokens each agent is given to start with. This was matched to the human game that was selected for the simulation. In the games that did not include an inequality condition, agents were allocated 20 tokens at the start of the game. When inequality was included in the human game, half of the agents were allocated 10 tokens with the other half receiving 30 tokens.

The second step was to define the weighting for each factor. In the current study, each of the six simulation factors were set to range between zero and one hundred. Increments of increase were set at fifty. The simulator would then run 40 rounds with one combination of factors and then run through every possible combination of the six factors with the three levels of 0, 50 and 100. The six factors with 3 levels resulted in 729 combinations of factor weightings. Each combination was repeated over 40 rounds.

One problem encountered with the simulator set to run these combinations was that when all factors were set to zero, a perfect predicted score was returned. Upon investigation it was revealed to be a mathematical problem that prevented this particular combination from being used. If the six matrices were all ranked zero, (the coefficients all being zero) upon multiplying, the values in the matrix became zero. During ranking, agents were given an equal rank of 1 and this returned a perfect predicted rank for each agent. A simple solution was to remove the condition where all factors were set to zero.

<u>Data output</u>

The data produced by the simulator detailed the comparison between the selected human experiment and the prediction derived from the Empathy Matrix (see Table 4). A round summary sheet was produced in excel that gave a summary of the predictions and comparisons for all 14 agents in each round. Each row supplied the following information;

- The experiment identifier, which was a code that identified a particular game with the experimental conditions used.

- The trial and round number for each row of data was then displayed.
- The factor weightings (simulator conditions) for each round were displayed, the percentage of correct predictions and the average scaled rank.
- The measures of how well the model predicted the moves of the human game were displayed as the ‘percent correct’ variable and the ‘Average Scaled Prediction’.

Table 3 : Comparison data

	A	C	D	E	H	I	J	K	L	M	N	O	P
1	Game Name	Round No.	Average Rank	Percent Correct	Average Scaled Prediction	Fairness weight	Reciprocity weight	Group Weight	self Interest weight	vicinity weight	Random value	Individual/Group	Equality/Inequality
119874	II01	33	[7.5 7.5 7.5 7.	0	0.40109890109890106	0	50	0	0	50	50	0	1
119875	II01	34	[7.5 7.5 7.5 7.	7.142857142857	0.45604395604395603	0	50	0	0	50	50	0	1
119876	II01	35	[7.5 7.5 7.5 7.	0	0.36263736263736257	0	50	0	0	50	50	0	1
119877	II01	36	[7.5 7.5 7.5 7.	7.142857142857	0.42857142857142855	0	50	0	0	50	50	0	1
119878	II01	37	[7.5 7.5 7.5 7.	0	0.3186813186813187	0	50	0	0	50	50	0	1
119879	II01	38	[7.5 7.5 7.5 7.	0	0.4010989010989011	0	50	0	0	50	50	0	1
119880	II01	39	[7.5 7.5 7.5 7.	7.142857142857	0.39560439560439553	0	50	0	0	50	50	0	1
119881	II01	40	[7.5 7.5 7.5 7.	0	0.3791208791208791	0	50	0	0	50	50	0	1
119882	II01	1	[7.5 7.5 7.5 7.	14.28571428571	0.5274725274725275	0	50	0	0	50	100	0	1
119883	II01	2	[7.5 7.5 7.5 7.	21.42857142857	0.532967032967033	0	50	0	0	50	100	0	1
119884	II01	3	[7.5 7.5 7.5 7.	14.28571428571	0.653846153846154	0	50	0	0	50	100	0	1
119885	II01	4	[7.5 7.5 7.5 7.	7.142857142857	0.565934065934066	0	50	0	0	50	100	0	1
119886	II01	5	[7.5 7.5 7.5 7.	7.142857142857	0.4945054945054946	0	50	0	0	50	100	0	1
119887	II01	6	[7.5 7.5 7.5 7.	14.28571428571	0.6208791208791208	0	50	0	0	50	100	0	1
119888	II01	7	[7.5 7.5 7.5 7.	7.142857142857	0.5659340659340659	0	50	0	0	50	100	0	1
119889	II01	8	[7.5 7.5 7.5 7.	0	0.4560439560439561	0	50	0	0	50	100	0	1
119890	II01	9	[7.5 7.5 7.5 7.	14.28571428571	0.5934065934065933	0	50	0	0	50	100	0	1
119891	II01	10	[7.5 7.5 7.5 7.	14.28571428571	0.5549450549450549	0	50	0	0	50	100	0	1
119892	II01	11	[7.5 7.5 7.5 7.	0	0.60989010989011	0	50	0	0	50	100	0	1
119893	II01	12	[7.5 7.5 7.5 7.	14.28571428571	0.5934065934065933	0	50	0	0	50	100	0	1
119894	II01	13	[7.5 7.5 7.5 7.	7.142857142857	0.5384615384615385	0	50	0	0	50	100	0	1
119895	II01	14	[7.5 7.5 7.5 7.	0	0.3846153846153846	0	50	0	0	50	100	0	1
119896	II01	15	[7.5 7.5 7.5 7.	14.28571428571	0.4835164835164835	0	50	0	0	50	100	0	1
119897	II01	16	[7.5 7.5 7.5 7.	21.42857142857	0.5604395604395604	0	50	0	0	50	100	0	1
119898	II01	17	[7.5 7.5 7.5 7.	28.57142857142	0.5714285714285714	0	50	0	0	50	100	0	1
119899	II01	18	[7.5 7.5 7.5 7.	7.142857142857	0.49450549450549447	0	50	0	0	50	100	0	1
119900	II01	19	[7.5 7.5 7.5 7.	0	0.4780219780219781	0	50	0	0	50	100	0	1
119901	II01	20	[7.5 7.5 7.5 7.	7.142857142857	0.5109890109890111	0	50	0	0	50	100	0	1
119902	II01	21	[7.5 7.5 7.5 7.	14.28571428571	0.6483516483516484	0	50	0	0	50	100	0	1
119903	II01	22	[7.5 7.5 7.5 7.	21.42857142857	0.521978021978022	0	50	0	0	50	100	0	1
119904	II01	23	[7.5 7.5 7.5 7.	14.28571428571	0.5274725274725275	0	50	0	0	50	100	0	1
119905	II01	24	[7.5 7.5 7.5 7.	7.142857142857	0.5604395604395603	0	50	0	0	50	100	0	1
119906	II01	25	[7.5 7.5 7.5 7.	0	0.434065934065934	0	50	0	0	50	100	0	1

The data produced by the simulator provides a mean of all 14 predictions in each round. The dependent variable 'Average Scaled Prediction' is visible here in column H. The factor weightings are visible in columns I through N.

The “Percent Correct” variable seen in column E of Table 4 is a measurement of how accurately the model has predicted human moves. The scope of measurement that this variable provides is limited as it only counts the number of perfectly predicted exchanges per round. The number of perfectly predicted exchanges out of a maximum of 14 is then displayed as a percentage.

The variable “Average Scaled Prediction” was selected as it provided a more accurate measure of the model’s performance. The model predicts each human participant’s move from 1 (perfect prediction) to 14 (furthest ranked participant from the participant that actually received the token). This variable then provided a method that quantified how close the model was to predicting human moves.

The Average Scaled Predictions for each round were calculated by firstly, identifying the particular agent to whom each player made an allocation. Secondly, determining the corresponding likelihood score. Thirdly, computing the average of the likelihood scores across all 14 players for each round. This measure then provided an overall average score of predictive accuracy for each round.

Data analysis

Descriptive statistics

A table of means of the dependent variable “Average Scaled Prediction” with each factor in isolation to each other was created using the “tapply” function in R (Team, 2014). This function allows a mean of the dependent variable to be calculated in reference to each level of a particular independent variable.

Multi-level model

The output data obtained from the simulator is hierarchical in nature, having games nested within experimental conditions. The assumption of independence is violated with this hierarchical data and consequently analytical methods such as analysis of variance would be inappropriate. The appropriate choice for hierarchical data sets is multi-level modelling (Quené & Van den Bergh, 2004). Multi-level modelling is a robust procedure that can handle moderate violations of homoscedasticity and sphericity. This analysis, compared with a repeated measure ANOVA provides more power in estimating the effects.

Researchers usually seek to accurately account for the influence that a selected independent variable has on the dependent variable. A danger to the interpretation of the results can occur when unexplained extraneous factors have an effect on the dependent variable and account for some of the variance. These random factors often do not have any theoretical interest yet it is important to account for these factors and the degree to which they influence the dependent variable (Albright & Marinova, 2010).

Using standard analysis of variance models with hierarchical data can lead to unrealistic parameter estimates as the errors between units in a level are likely correlated (Albright & Marinova, 2010). In order to assess the correlation between level 2 conditions (games), an interclass correlation coefficient was calculated. In this case of the current study, the intraclass correlation coefficient was 0.06 at the game level. This means that 6% of the variance in the dependent variable can be explained by variance between the mean scores of games. An advantage for the use of multilevel modelling is that it would be able to account for this random variance and allow a more precise inference of the fixed effects (Quené & Van den Bergh, 2004).

The Netlogo simulator was coded to be able to run every possible combination of the six modelled exchange rules at three levels of 0, 50 and 100 for each human game. Every time the Netlogo simulator was run, a human game was uploaded and the simulator then ran a simulation for each combination of exchange rules at the three levels of weightings. A human game consisting of 40 rounds multiplied by 6 factors at three levels (40×3^6) resulted in a round summary sheet with 29160 rows of data. Each row of data was a summary of one round of play. The 40 rounds of data where the factor weightings were set to zero were removed which then resulted in a simulator output of 29120 rows of data. In order to analyse all of the simulations under one analysis, it was necessary to collate the sixteen datasets into one data set that could be imported into R. The data were then analysed using the “lme4” package in R (Bates, Mächler, Bolker, & Walker, 2014).

Chapter 4: Results

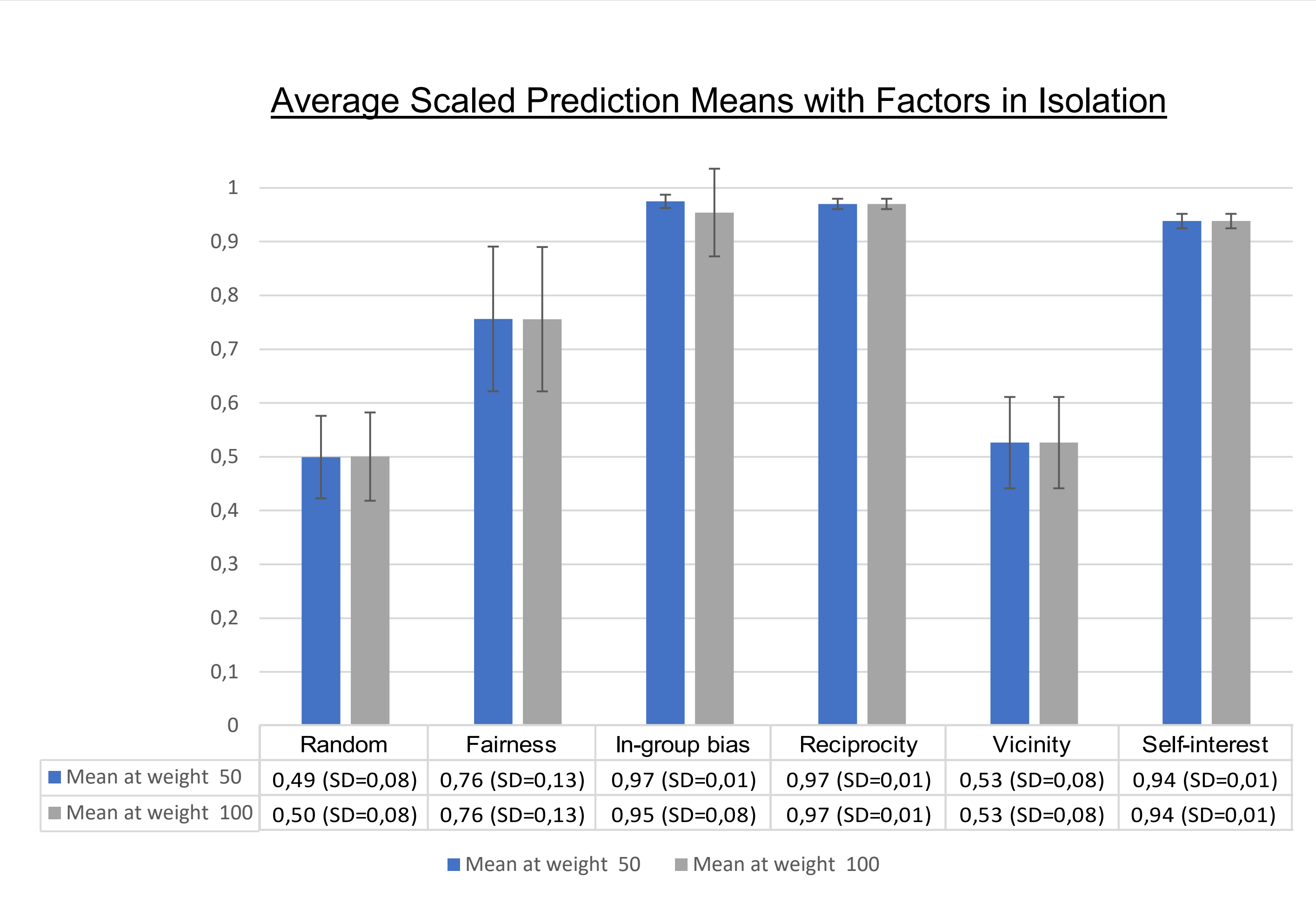
The results chapter is separated into four components. The first section addresses the question: Is prediction accuracy different over the six simulator conditions? The second section describes the multi-level model. The third section addresses the question: Do the simulator conditions lead to different levels of prediction accuracy over the four experimental conditions? Finally, the fourth section addresses the question: Which combination of simulator factors best predict human decision making in the four experimental conditions?

Section 1: Effects of simulated factors in isolation across 16 games

The primary aim of this section is to answer the question of whether prediction accuracy is different across simulated conditions. In order to achieve this, simulations had to be run for one factor at a time with all other factors excluded. This meant that only one factor contributed towards the Empathy Matrix in each simulation. Each factor was tested at two weightings of 50 and 100 with all other factors set to zero. The simulations were repeated over all 16 human games.

Figure 4 represents the means for the dependent variable, Average Scaled Prediction, for each simulator condition at each level of weighting over 16 games. The error bars represent the standard deviation of the accuracy score for each factor weighting.

Figure 4: Mean prediction accuracy with factors in isolation



The expected value for the dependent variable “Average Scaled Prediction” is the mean of the 14 predicted ranks (see Table 2) which is (M = .50, SD = 0.31). This means that if ranks were allocated randomly between 14 agents, the likelihood of an agent receiving any particular rank would be 0.5. This value then provides a theoretical baseline where in the case where every move was random, the expected value would be 0.5.

As seen in Figure 4, the random weight at weight 50 (M = .49, SD = 0.08) and weight 100 (M = .50, SD = 0.08) is equal to the expected value. This provides assurance that the methodology is sound and that a meaningful prediction would range between .5 and 1. The random factor, as it is not effectively modelling human behaviour was removed from the model in order to gain theoretically meaningful results from the simulations.

The vicinity factor at weight 50 (*M* = .53, *SD* = 0.08) and weight 100 (*M* = .53, *SD* = 0.08) had a poor effect on prediction accuracy. The fact that these factors lead to prediction accuracy of around .5 implies that they are of very little theoretical importance in modelling human decision making in the VIAPPL games. These results provide rationale for removing these two factors from the agent-based model. It is expected that the exclusion of these two factors would lead to greater sensitivity in the final multi-level model analysis.

The factors that led to the highest prediction accuracy were ingroup favouritism, reciprocity and self-interest. Reciprocity in both weights of 50 and 100 yielded a prediction accuracy of (*M* = .97, *SD* = 0.01). The standard deviations for reciprocity are very low which means that there is little variation in individual scores from the mean. This may indicate that reciprocity is a reliable factor in the agent-based model. Ingroup favouritism was more accurate at weight 50 (*M* = .97, *SD* = 0.01) than at weight 100 (*M* = .95, *SD* = 0.08). The standard deviation at weight 50 was much lower than at weight 100 which may indicate that ingroup favouritism, at weight 50, is more reliable with less variation between scores. Self-interest at both weights of 50 and 100 led to a prediction accuracy of (*M* = .94, *SD* = 0.01). The standard deviations for both weights of self-interest were low which indicates that it is a reliable factor relative to the other factors. Fairness was less accurate than reciprocity, self-interest and ingroup favouritism and had a mean prediction accuracy of (*M* = .76, *SD* = 0.13) at both weights of 50 and 100.

The reason fairness has a lower accuracy score to the higher scoring factors is due to the way fairness has been operationalised. Note that in Figure 3, the accuracy scores for ingroup favouritism, reciprocity and self-interest are in the range of .92 and 1 (between rank 1 and 2). These high values, in comparison with fairness, are due to the fact that the measure of ingroup favouritism, reciprocity and self-interest are binary outcomes. Agents either gave to their ingroup or not, they either self-gave or they did not, and they either reciprocated or they did not. When these binary factors were used in a simulation without a factor that had more than two possible outcomes, the Average Scaled Prediction would be limited to the range between ranks 1 and 2. Fairness has a much larger variance with all 14 players being possibilities, therefore the ranks can have a maximum range of 14. The scale of the measure of accuracy dramatically increases when fairness is included and when this factor is removed, the scale becomes far smaller. This effect has made comparisons between these simulations misleading.

The standard deviation for self-interest was relatively high in comparison to these higher scoring factors. This may indicate that self-interest in addition to being a lower scoring factor, is less reliable with more variation between scores.

The simulations were then run including every combination of fairness, ingroup favouritism, reciprocity and self-interest as contributors to the deciding Empathy Matrix. The removal of the random factor along with the proximity factor reduced the size of the resulting data considerably. With 4 factors at 3 levels (3^4) the total number of combinations were reduced to 81. The condition with every factor set to zero was removed which led to 80 combinations repeated over 40 rounds for each of the sixteen human games. The resulting data set then amounted to 51,200 round level comparisons.

Section 2: Multilevel model

The dependent variable, Average Scaled Prediction, is a value between 0 and 1. Due to the fact that the expected value is .5, any meaningful results lie in the range between .5 and 1. This resulted in the dependent variable being negatively skewed. This pattern violated the assumption of normality for conducting a multi-level analysis. In order to proceed with the analysis, the data were transformed using an arcsine transformation (see Figure 5 and 6).

Figure 6: Histogram of the dependent variable Average Scaled Prediction

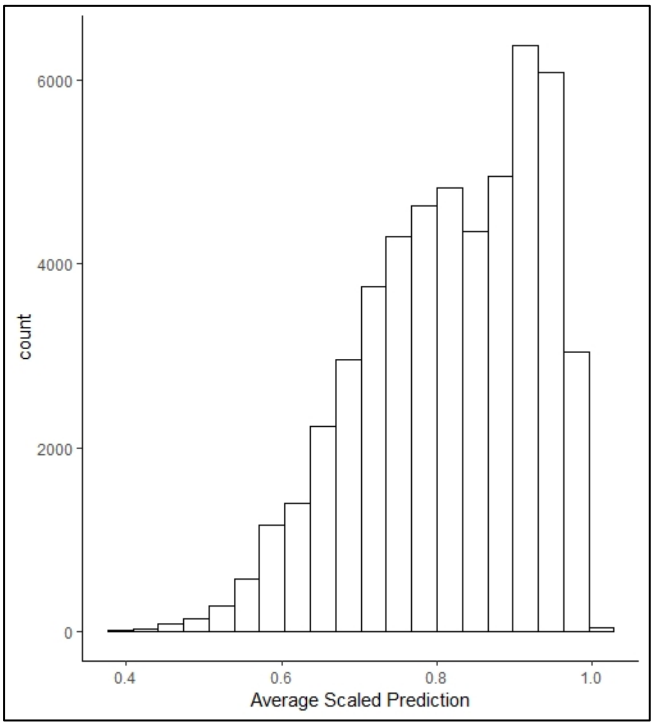
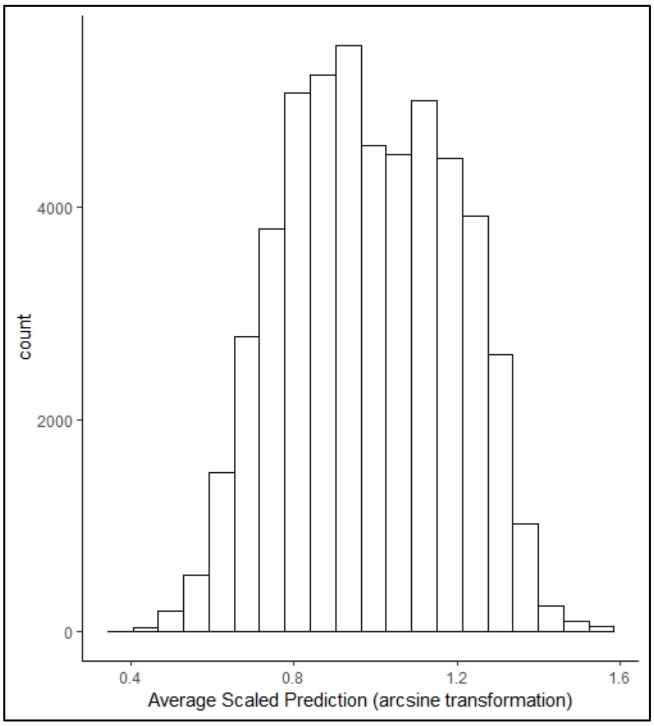


Figure 5: Histogram of the dependent variable Average Scaled Prediction after transformation



One consequence of using a transformation to satisfy the assumption of normality is that the original scale of the dependent variable is lost (Lo & Andrews, 2015). Interpretation then becomes difficult as one cannot relate the new values to the original scale. Two methods were used in order to combat this problem, firstly a second analysis was run with the original untransformed variable which would supply beta regression coefficients in the original scale. These coefficients were reported in conjunction with the coefficients from the transformed data. Secondly, a table is provided with the original scaled prediction ranks with the arcsine transformed equivalents in a corresponding column (see table 5). This table then visualises the comparable transformed dependent variable to the original scale.

Table 4: Arcsine transformed prediction ranks

	Predicted Rank	Predicted Rank (Arcsine)
1	1	1.5707963267949
2	0.923077	1.17600540709518
3	0.846154	1.00872681246447
4	0.769231	0.877636780375781
5	0.692308	0.76468260426419
6	0.615385	0.662874311600265
7	0.538462	0.568610847986836
8	0.461538	0.479728117409841
9	0.384615	0.394790703033131
10	0.307692	0.312766398560729
11	0.230769	0.232867941087265
12	0.153846	0.154459442784397
13	0.076923	0.0769990635051488
14	0	0

Note. The scaled prediction rank is the value that is obtained by comparing the human players move to that of the simulated agent. Predicted rank 1 refers to a perfect prediction where an agent move has perfectly matched that of the human participant.

Model building

Since the data were hierarchical in nature, required attention was given to the specific nesting structure. The data were structured with games being nested within experimental conditions. Therefore, a null model was built with a random intercept at the game level. The intraclass correlation coefficient was 0.06 which meant that 6% of unexplained variance was the game level. This amount of random variance is not extremely high however it is high enough to justify the use of a multilevel model.

The next model built was a model with the random intercept at the game level with the simulator factors and experimental factors added. This model proved a better fit than the null model.

The third model was built with three-way interactions between each simulator factor and the two experimental conditions of groups and inequality. This model was theoretically motivated as it would allow the observation of the relative importance of each exchange rule under each of the four experimental conditions. This model proved to be a better fit than the null model and the model with main effects. Table 6 displays the comparisons between the three models.

Table 5: Model Comparisons

Model Name	Model Description	BIC	Significance test
Null model	Intercept only	-20145	
Main effects	Null + Reciprocity + Fairness+ Self-interest + Group	-71668	$\chi^2(10) = 51631.1$, $p < 0.001$
Interaction effects	Main + Individual.Group*Equality.Inequality + all 3-way interactions of Individual.Group*Equality.Inequality BY Reciprocity, Fairness, Self-interest and Group.	-79669	$\chi^2(25) = 8272.8$, $p < 0.001$

It should be noted that the model including three-way interactions has a much lower BIC value than the null model and the model with main effects. This lower BIC value indicates a better fit to the data. The Chi-square test for the final model ($\chi^2(25) = 8272.8$, $p < 0.001$) indicates that the difference is significant.

The intercept for the final model with three-way interactions was ($\beta = 1.302$, $SE = 0.015$, $p < .001$). For interpretation, the intercept for the same model with the untransformed dependent variable is ($\beta = 0.983$, $SE = 0.010$, $p < .001$). This can be considered the expected mean for the dependent variable, Average Scaled Prediction. Thus, the expected mean of the variable Average Scaled Prediction is .98.

The beta coefficients for each fixed effect represent the increase or decrease that would be observed in the expected score (the intercept) of the dependent variable with a one unit increase in the predictor, with all other predictors held constant (Albright & Marinova, 2010). The ANOVA summary table (Table 7) of fixed effects is displayed below. The summary table for the comparisons between categories can be found at Appendix 1.

Table 6: Multilevel model with three-way interactions

Type III Analysis of Variance Table with Satterthwaite's method

Fixed effects:	**Sum Sq**	**Mean Sq**	**NumDF**	**DenDF**	**F value**	**Pr(>F)**
Individual.Group	0.01	0.01	1	16	0.7491	0.3995443
Equality.Inequality	0.04	0.04	1	16	3.4715	0.0808969 .
Reciprocity.weight	0.37	0.19	2	51184	15.1555	2.630e-07 ***
self.Interest.weight	14.51	7.26	2	51184	593.2612	< 2.2e-16 ***
Group.Weight	15.49	7.75	2	51184	633.2602	< 2.2e-16 ***
Fairness.weight	1264.43	632.21	2	51184	51683.6841	< 2.2e-16 ***
Individual.Group:Equality.Inequality	0.33	0.33	1	16	26.8503	9.088e-05 ***
Individual.Group:Reciprocity.weight	0.02	0.01	2	51184	1.0030	0.3668016
Equality.Inequality:Reciprocity.weight	0.53	0.27	2	51184	21.7849	3.491e-10 ***
Individual.Group:self.Interest.weight	5.76	2.88	2	51184	235.4504	< 2.2e-16 ***
Equality.Inequality:self.Interest.weight	11.90	5.95	2	51184	486.5757	< 2.2e-16 ***
Individual.Group:Group.Weight	25.36	12.68	2	51184	1036.4657	< 2.2e-16 ***
Equality.Inequality:Group.Weight	18.60	9.30	2	51184	760.3994	< 2.2e-16 ***
Individual.Group:Fairness.weight	0.96	0.48	2	51184	39.0571	< 2.2e-16 ***
Equality.Inequality:Fairness.weight	19.16	9.58	2	51184	783.0238	< 2.2e-16 ***
Individual.Group:Equality.Inequality:Reciprocity.weight	0.22	0.11	2	51184	9.0507	0.0001175 ***
Individual.Group:Equality.Inequality:self.Interest.weight	0.12	0.06	2	51184	5.0152	0.0066398 **
Individual.Group:Equality.Inequality:Group.Weight	1.36	0.68	2	51184	55.7155	< 2.2e-16 ***
Individual.Group:Equality.Inequality:Fairness.weight	23.77	11.88	2	51184	971.5869	< 2.2e-16 ***

Note. *p<0.1; **p<0.05; ***p<0.001.

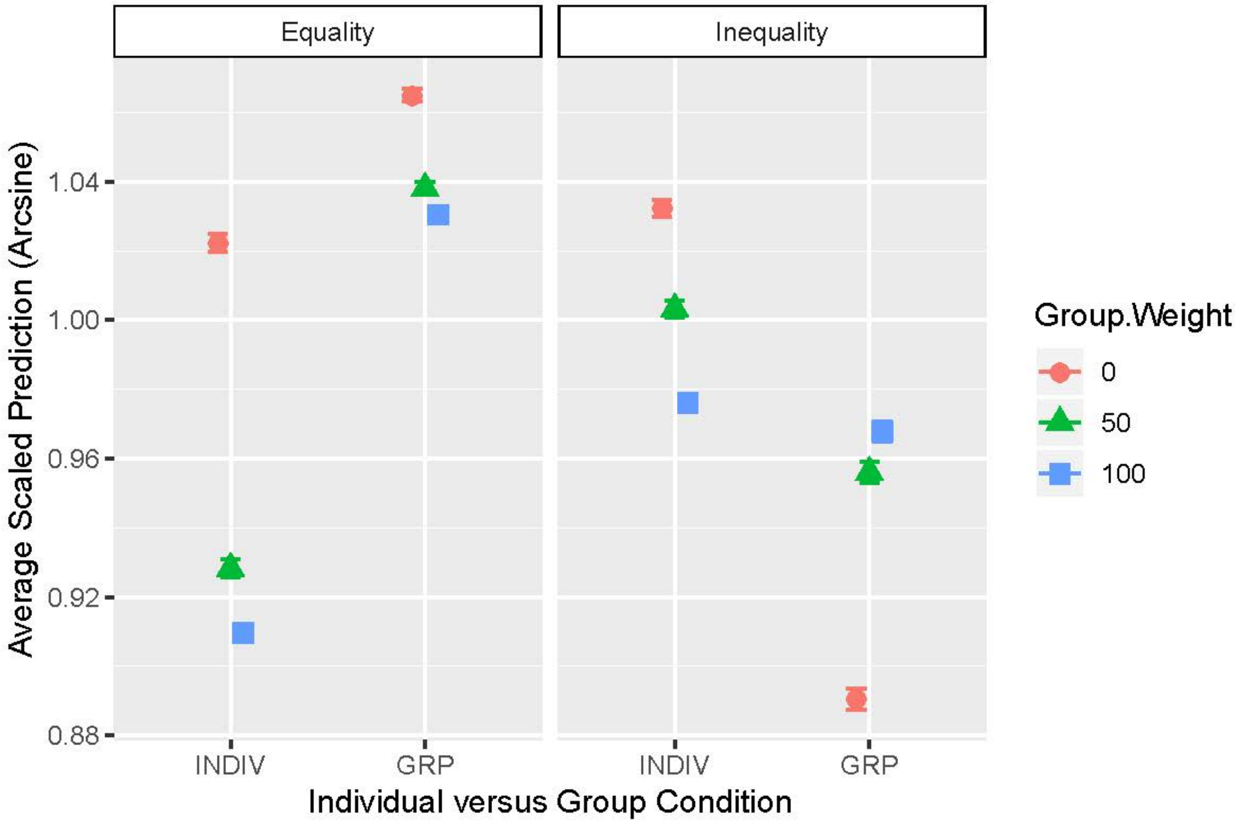
Note. The p-values for main effects and interactions are mostly significant. This effect is likely attributable to the large sample size.

Section 3: Effects of simulated factors across experimental conditions.

The primary aim of this section is to answer the question: In which experimental condition does each simulator factor lead to higher prediction accuracy? The necessity of this analysis is due to the fact that human exchange behaviour differs under the various experimental conditions. We therefore expected theoretically interesting interactions to occur between the simulator conditions and the four experimental conditions.

In order to interpret these three-way interactions, it was necessary to create visualised representations of the interactions. Three-way interaction graphs were created from the final multi-level model using R's predict function to calculate the mean model predictions and their standard errors. The "ggplot2" function was then used to create graphs that depicted these interactions (Wickham, 2016).The points in each graph represent the mean model predictions in each weighting of the independent variable. These means were created by calculating the average prediction accuracy over the entire dataset. The error bars represent the standard errors of the predictions.

Figure 7: Three-way interaction between the group condition, the inequality condition and the manipulation of the ingroup favouritism weighting.



Note. *F* (2, 51184) = 55.72, *P* = < 0.001

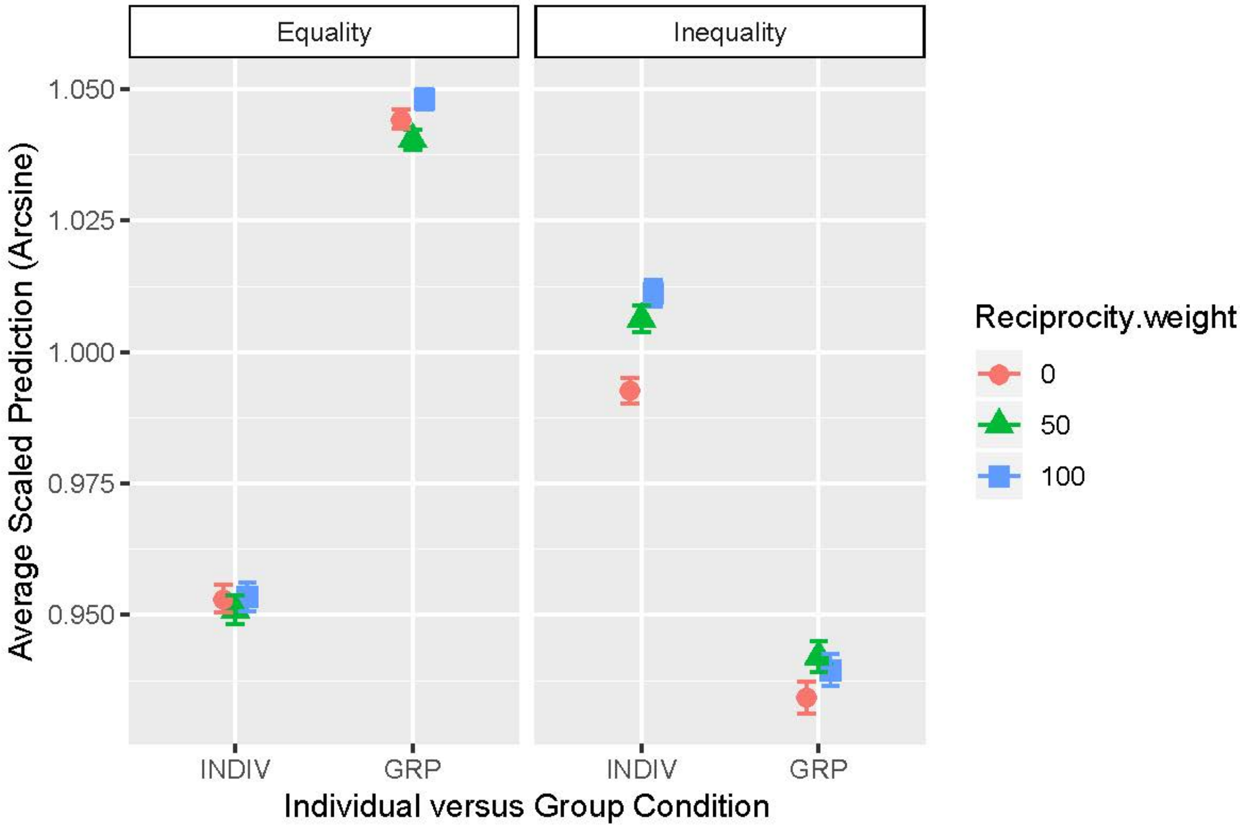
The interaction between ingroup favouritism with the group and inequality conditions, when weighted at 50, had a statistically significant effect on prediction accuracy in comparison to simulations with ingroup favouritism weight set to zero (β = 0.023, *SE* = 0.005, $p < .001$). Ingroup favouritism weighted at 100 was also statistically significant accuracy in comparison to simulations with ingroup favouritism weight set to zero (β = 0.051, *SE* = 0.005, $p < .001$). For interpretation, the coefficients from the analysis with the untransformed dependent variable are given. Ingroup favouritism at weight 50 was (β = 0.015, *SE* = 0.003, $p < .001$) and at 100 was (β = 0.030, *SE* = 0.003, $p < .001$). This means that at weight 50, the predicted mean would increase .015 for every one unit increase in ingroup favouritism weight with all other independent variables held constant. At weight 100, the increase would be .030.

It is noted that in both individual conditions, increasing the weighting of ingroup favouritism leads to reduced prediction accuracy. This is a logical and expected outcome as group membership was not visible to the human participants. An interesting note is that the individual condition under the inequality condition leads to a lesser reduction in accuracy than the individual condition under equality. A potential explanation for this could be that in the inequality condition, though groups were not visible, there existed a high and low status group visible by each participant's token balance. This could have led to a weaker process of social categorisation which subsequently led to ingroup favouritism.

The equal status group condition led to reduced prediction accuracy with an increase in ingroup favouritism weighting. The accuracy scores under this condition are high as seen by the relative position of the data points on the y-axis. The decrease in prediction accuracy leads us to the conclusion that another factor is responsible for this accuracy. The results of analysis 3 confirm that reciprocity in this condition was a more important factor in predicting human moves (See Figure 12). As ingroup favouritism was reduced, reciprocity was able to become more evident.

The weighting of ingroup favouritism under the unequal group condition led to an increase in prediction accuracy. This means that ingroup favouritism was a powerful determinate of the decision making in token allocation.

Figure 8: Three-way interaction between the group condition, the inequality condition and the manipulation of the reciprocity weighting

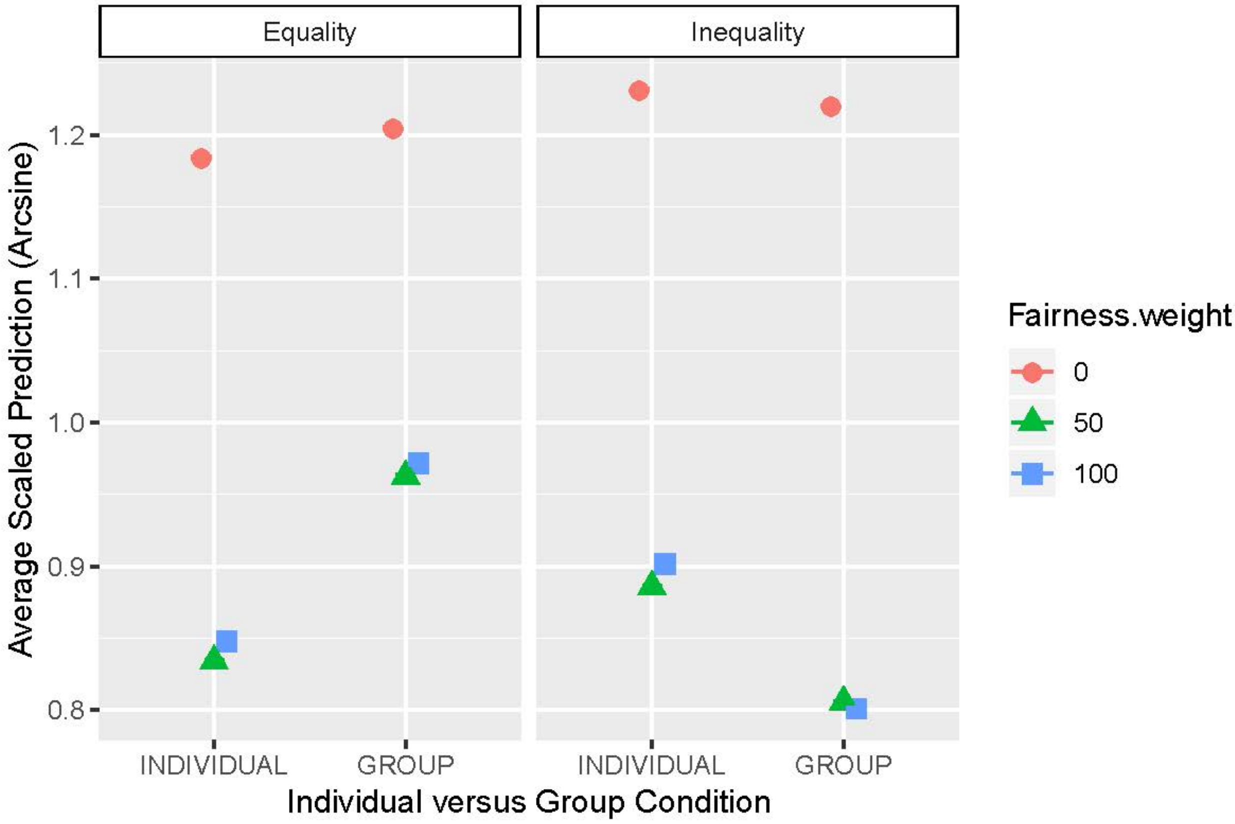


F (2, 51184) = 9.05, *P* = < 0.001

The interaction between reciprocity with the group and inequality conditions, when weighted at 50, did not have a statistically significant effect on prediction accuracy in comparison to simulations with reciprocity weight set to zero (*β* = -0.008, *SE* = 0.005, *p* = 0.10760). Reciprocity weighted at 100 did however have a significant effect on the dependent variable in comparison to simulations with reciprocity weight set to zero (*β* = -0.020, *SE* = 0.005, *p* < .001). For interpretation, the coefficients from the analysis with the original dependent variable are given. Reciprocity at weight 50 was (*β* = -0.006, *SE* = 0.003, *p* = 0.4440) and at 100 was (*β* = -0.012, *SE* = 0.003, *p* < .001).

The weighting of reciprocity has, in most conditions, resulted in very little difference in prediction accuracy. It is noted that the weighting of reciprocity in the individual inequality condition, leads to an increase in prediction accuracy.

Figure 9: Three-way interaction between the group condition, the inequality condition and the manipulation of the fairness weighting

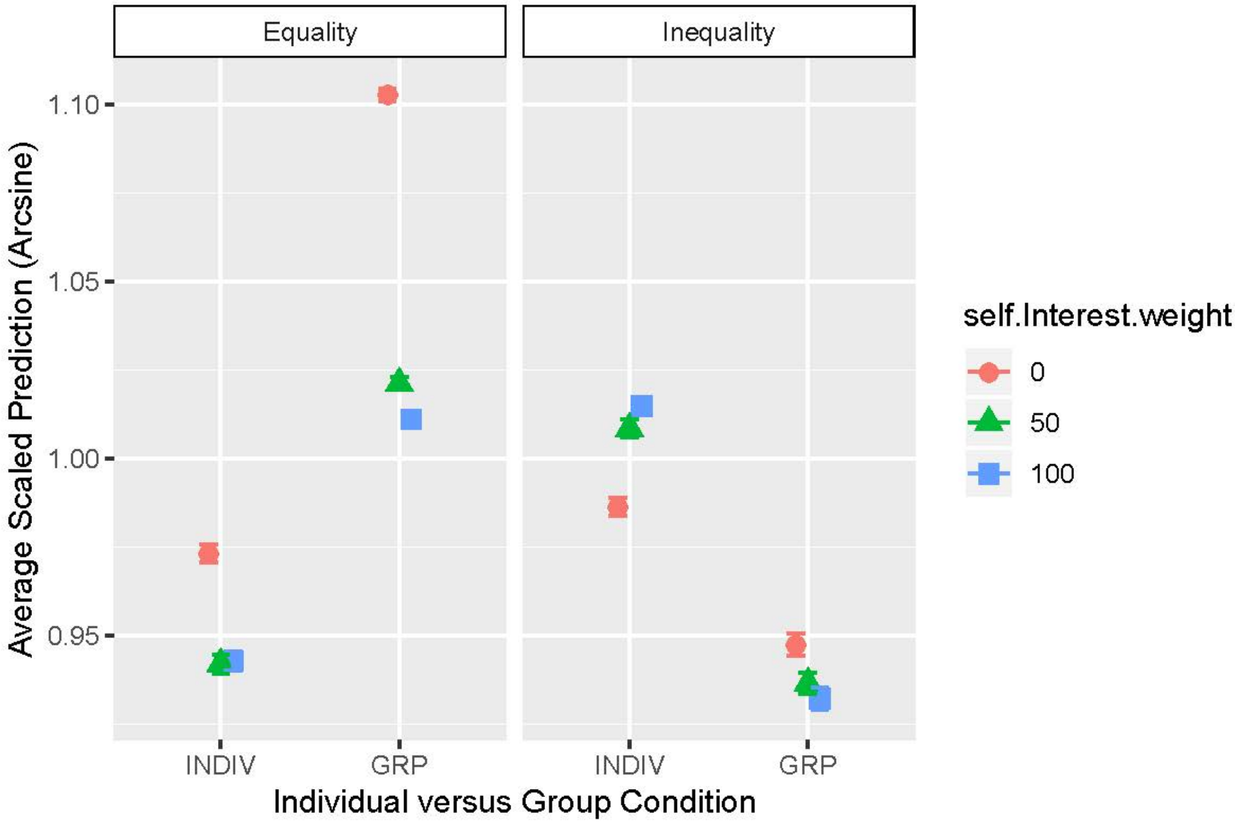


Note. *F* (2, 51184) = 971.58, *P* = < 0.001

The interaction between fairness with the group and inequality conditions, when weighted at 50, had a statistically significant effect on prediction accuracy in comparison to simulations with fairness weight set to zero (β = -0.176, *SE* = 0.005, *p* < .001). Fairness weighted at 100 was also statistically significant in comparison to simulations with fairness weight set to zero (β = -0.191, *SE* = 0.005, *p* < .001). For interpretation, the coefficients from the analysis with the original dependent variable are given. Fairness at weight 50 was (β = -0.123, *SE* = 0.003, *p* < .001) and at 100 were (β = -0.131, *SE* = 0.003, *p* < .001). The beta coefficients are far larger than most of the three-way interactions reported. The coefficients are negative which indicates a reduction in prediction accuracy.

The fairness factor as had negative effect on prediction accuracy over all four experimental conditions. The fairness factor, when weighted in all four experimental conditions, leads to a reduction in prediction accuracy. The prediction accuracy as noted on the y-axis, drops from 1.2 to under 1 on the arcsine transformed scale (please refer to Table 5) when fairness is introduced. This means that with fairness excluded, the average rank falls between position 1 and 2 and when fairness is included, the rank drops to position 4. This effect is attributable to the previously discussed problem of fairness being mathematically disadvantaged in comparison to the three other decision rules with binary outcomes.

Figure 10: Three-way interaction between the group condition, the inequality condition and the manipulation of the self-interest weighting



Note. F (2, 51184) = 5.02, P = 0.0066398

The self-interest weighting, when weighted at 50, had a statistically significant effect on prediction accuracy in comparison to simulations with self-interest weight set to zero (β = 0.013, SE = 0.005, p < .001). Self-interest weighted at 100 was also statistically significant in comparison to simulations with self-interest weight set to zero (β = 0.013, SE = 0.005, p < .001). For interpretation, the coefficients from the analysis with the original dependent variable are given. Self-interest at weight 50 was (β = 0.005, SE = 0.003, p = 0.05337) and at 100 were (β = 0.006, SE = 0.003, p = .05227). These coefficients are small which indicates that self-interest did not make a large impact on prediction accuracy.

The weighting of self-interest had a positive effect on prediction accuracy in the individual condition with inequality. This finding suggests that self-giving was common in the human game and the higher the weighting in the agent-based model, the more the data matched that of the human game. In the remaining three conditions, the weighting of self-interest led to a decrease in accuracy, an interesting note is the difference between these three conditions. The weighting of self-interest in the group condition without inequality had the largest difference in prediction accuracy. Self-interest weighted in this condition reduced accuracy. The fact that self-interest reduced accuracy to this extent suggests that self-giving was not common in the human games under this experimental condition. The measured prediction accuracy in this condition is likely attributable to another factor. The reduction in weighting of self-interest allowed the better predicting factor to be more evident.

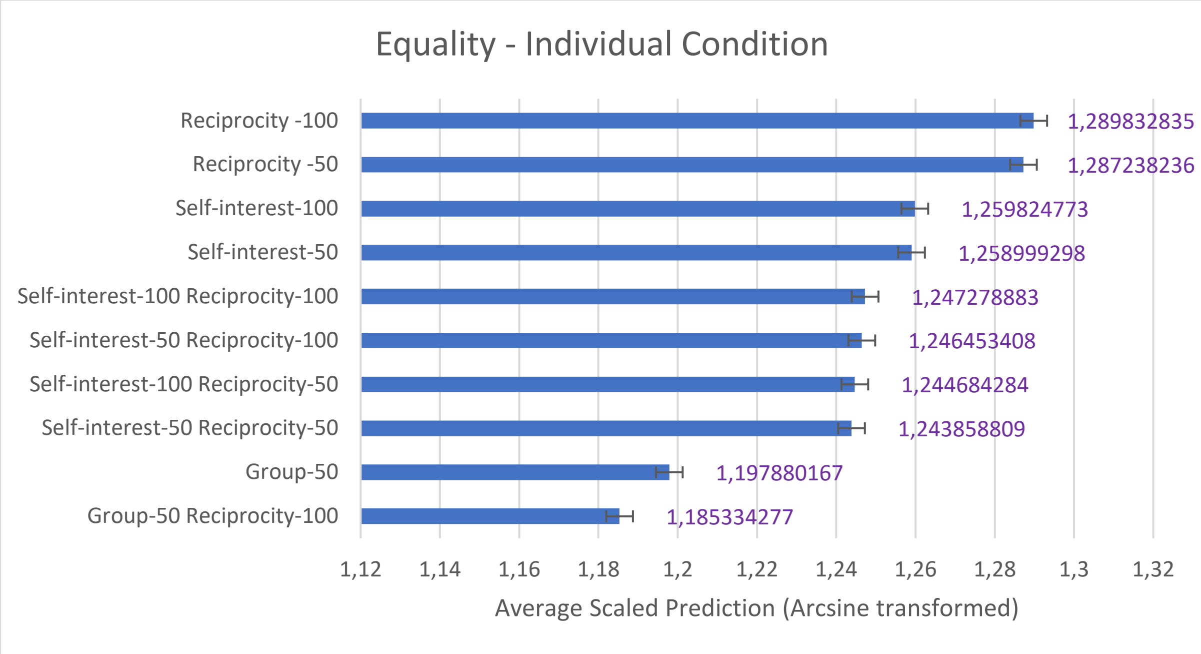
Section 4: The best fitting combination of factors in each of the four experimental conditions.

The primary aim of this section is to answer the question of which combination of factors best predicts the data of the human games under the four experimental conditions. The top ten combinations are reported for each experimental condition.

In order to obtain the best predicting combinations, the data were ranked based on accuracy. The data structure is as follows; there are four simulator factors each with three levels. These factors, when crossed in every possible combination, result in a total of 81 combinations. The combination with all four factors set to zero was removed as it resulted in a mathematical error. Each combination was repeated over 40 rounds for each of the sixteen human games, this resulted in a total number of 51,200 measurements.

The predict function in R was used to calculate predicted values, these were then inserted into a new column in the data frame. The data were then aggregated at the game level which gave a mean prediction accuracy for each combination. The data were then ranked based on the predicted values from most accurate to least accurate. The top ten combinations for each experimental condition were used to create the visualisations below. Each bar represents the transformed dependent variable, average scaled prediction, for each factor combination. The error bars represent the standard errors of the predicted values.

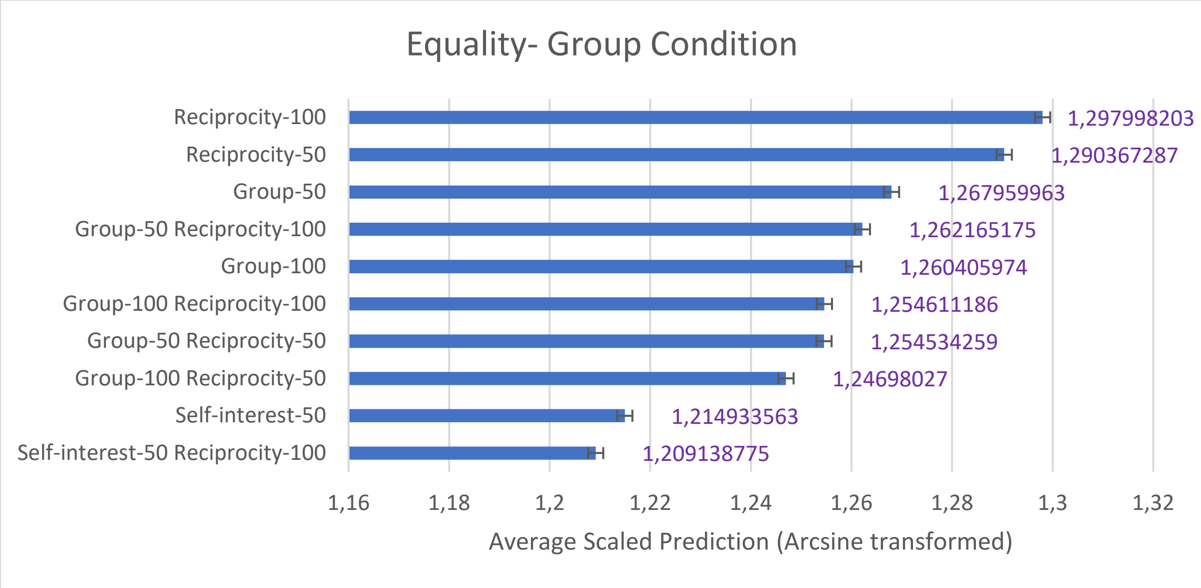
Figure 11: The best fitting combinations for the equal status individual condition



In the equal status individual condition, the most accurate simulator factor for matching the simulated data to that of the human games was reciprocity. Reciprocity at weight 100 yielded a prediction accuracy of (*M* = 1.289, *SE* = 0.003368). The second highest prediction was reciprocity weighted at 50 (*M* = 1.287, *SE* = 0.003368). The third highest was self-interest weighted at 100 (*M* = 1.259, *SE* = 0.003368).

The most accurate predictions in this experimental condition were single factors in isolation from other factors. When two or more factors were combined, prediction accuracy dropped substantially. It is noted that the inclusion of ingroup favouritism had a negative effect on prediction accuracy in this condition, this effect is visible in the three-way interaction graph (Figure 7). The fairness factor when included in isolation, at weight 100, reduced prediction accuracy to the point that it was ranked position 28 and had a mean accuracy of (*M* = 0.962, *SE* = 0.003368).

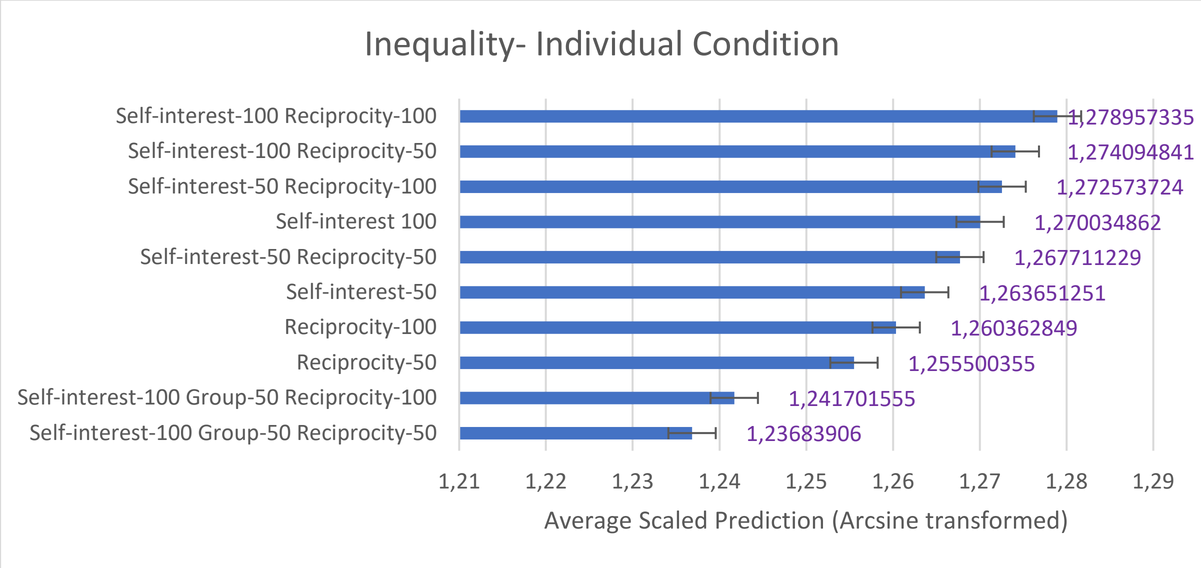
Figure 12: The best fitting combinations for the equal status group condition



In the equal status group condition, the most accurate simulator factor for matching the simulated data to that of the human games was reciprocity. Reciprocity at weight 100 yielded a prediction accuracy of (M = 1.298, SE = 0.001164). The second highest prediction was reciprocity weighted at 50 (M = 1.290, SE = 0.001164). The third highest was ingroup favouritism weighted at 50 (M = 1.268, SE = 0.001164).

The most accurate predictions in this condition can be attributed to reciprocity and ingroup favouritism. Reciprocity is more effective weighted at 100 than 50. Of interest is that ingroup favouritism weighted at 50 leads to a better prediction than if it were weighted at 100. Self-interest, when included in this experimental condition, results in a notable reduction in prediction accuracy. The fairness factor when included in isolation, at weight 100, reduced prediction accuracy to the point that it was ranked position 28 and had a mean accuracy of (M = 1.067, SE = 0.001164).

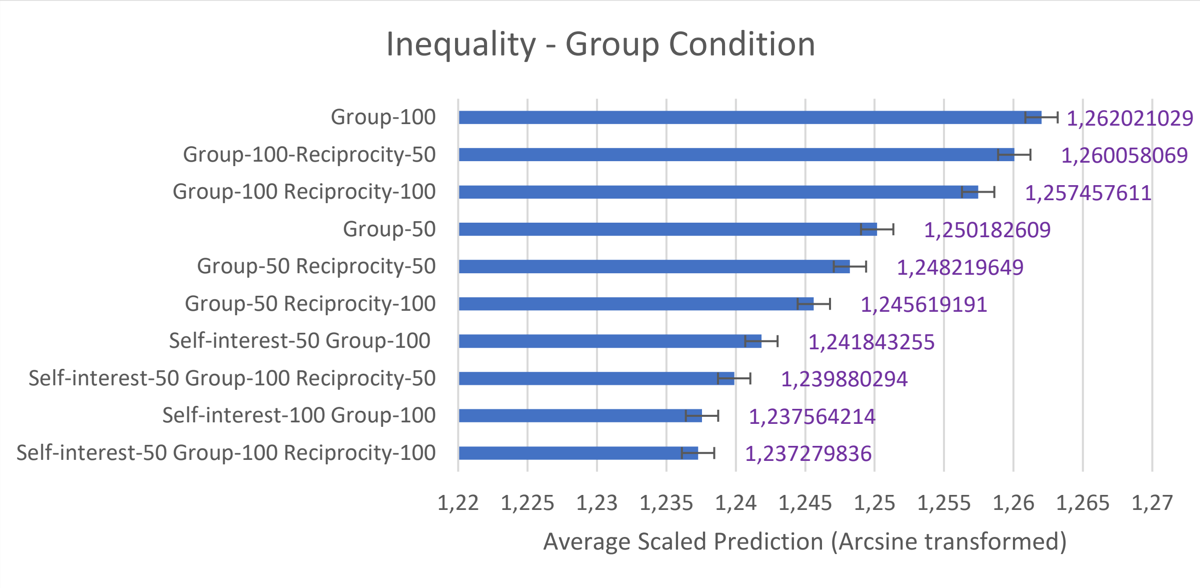
Figure 13: The best fitting combinations for the unequal status individual condition



In the unequal status individual condition, the most accurate simulator factors in matching the human data was a combination of self-interest and reciprocity. Reciprocity and self-interest both weighted at 100 yielded a prediction accuracy of (M = 1.279, *SE* = 0.00273). The second and third place in accuracy were different combinations of these two factors. Self-interest at weight 100 in isolation (*M* = 1.270, *SE* = 0.00273) led to a higher prediction accuracy than reciprocity at weight 100 in isolation (*M* = 1.260, *SE* = 0.00273).

Referring back to Figure 8 and Figure 10, it is noted that in the section of the plot that displays individual condition with inequality, both self-interest and reciprocity led to higher prediction when the weighting was increased. In the current visualisation, it is evident that a combination of these two factors tend to strengthen each other and together lead to a higher prediction accuracy than if they were in isolation. Ingroup favouritism, when weighted at 50 in isolation to other factors ranked position number 19 with a mean prediction accuracy of (*M* = 1.214, *SE* = 0.00273). The inclusion of the fairness factor in this experimental setting led to a dramatic decline in prediction accuracy. The fairness factor when included in isolation, at weight 100, reduced prediction accuracy to the point that it was ranked position 41 and had a mean accuracy of (*M* = 0.921, *SE* = 0.00273).

Figure 14: The best fitting combinations for the unequal status group condition



In the unequal status group condition, the most accurate simulator factor for matching the simulated data to that of the human games was ingroup favouritism. Ingroup favouritism at weight 100 yielded a prediction accuracy of (M = 1.262, SE = 0.00116). The second highest prediction was a combination of ingroup favouritism weighted at 100 and reciprocity weighted at 50 (M = 1.260, SE = 0.00116). The third highest combination was ingroup favouritism weighted at 100 and reciprocity weighted at 100 (M = 1.257, SE = 0.00116).

Ingroup favouritism was the best predictor of human behaviour in this experimental setting. This finding is also present in Figure 7 where an increase in the weighting of ingroup favouritism led to a higher rates of prediction accuracy. The combination of ingroup favouritism and reciprocity has also led to high prediction rates.

The self-interest factor tended to reduce prediction accuracy. Self-interest at weight 50 combined with ingroup favouritism at weight 100 has been ranked in position 7 with a mean prediction accuracy of (M = 1.242, SE = 0.00116). The fairness factor when included in isolation, at weight 100, reduced prediction accuracy to the point that it was ranked position 67 and had a mean accuracy of (M = 0.778, SE = 0.00116).

Chapter 5: Discussion

Exchange is a critical part of human interaction and for this reason social exchange theory has been a major area of focus in the field of social psychology. The ability for this theory to provide a framework to understand social structure has been demonstrated since Homans' early work in 1958. One area of social exchange theory that has in the past been critiqued is the dominant assumption of rationality that was mainly argued by Homans (1958). Meeker (1971) argued that rationality is an important factor, yet it should be given a far narrower definition than it has enjoyed in the past. She goes on to argue how multiple situations exist whereby rationality, in its primitive definition, is constrained. Emerson (1976) echoed this view and argued that the weighing up of rewards is an explanation for some exchange situations, but not all. Rationality could rather be thought of as an individual having weighed up the consequences associated with a particular exchange, but not necessarily make their decision based solely on profit maximisation. There are many cases whereby individuals do seem to act irrationally in the economic sense, fairness considerations being an illustrative example (Fehr & Schmidt, 1999).

Meeker (1971) sought to explain exchanges as decisions made by individuals faced with a potential exchange. In her schema, the problem of rationality is removed entirely. Rational choices, or simply profit maximisation, could then be treated as just a possible orientation used by individuals in certain situations (Emerson, 1976). Meeker went on to define five exchange rules of reciprocation, ingroup gain, competition, altruism, and status consistency. These exchange rules are argued to be normative and as such they will change based on the context of the situation. It can be expected that they may, in certain contexts, be supportive of one another; meaning individuals may select and use more than one exchange rule at a time. It is also expected that under some conditions, certain exchange rules will be at conflict with a larger governing norm. The process in which an individual adopts a particular exchange rule over the alternatives is a complex one and warrants a brief discussion on norms in general.

Norms are socially sanctioned behaviour in response to a particular stimulus. Norms are agreed upon socially and are maintained by approval for following the norm or disapproval if the norm is violated. At the personal level, anxiety and guilt resulting from the fear of punishment results in an internalisation of the norm. This internalisation can even guide behaviour when there is no one around to impose punishment for violating the norm. Elster (1989) uses an example of people adhering to a norm against picking one's nose in front of strangers that they will never see again. The strangers will never be able to impose punishments, yet people ordinarily will be sure not to violate this norm. This suggests that norms have great power in guiding individual behaviour due to the strong emotions that they illicit (Festre, 2010).

Norms within the VIAPPL exchange environment may be formal or informal. Meeker (1971) gives examples of informal norms, such as following norms that are followed by others, commitments that are formed through repeated exchange, or simple imitation of others around them. Formal norms could include role expectations or expectations of which exchange rule would be normative for a particular relationship. Ingroup favouritism, for example, is argued to be a dominant societal norm that prescribes ingroup favouring behaviour in a new and novel group situation (Iacoviello & Spears, 2018).

In the current research, a reconceptualised set of exchange rules has been proposed, drawing on recent research in exchange. Reciprocity, fairness, proximity, self-interest and ingroup favouritism have received recent empirical support and have been selected as candidates for an accurate model of social exchange.

Cropanzano et al. (2005) raised an important point; that very little research has examined the "black box" of social exchange. That is, the actual process of exchange has yet to be fully uncovered. Agent-based modelling has been used in the current research to model exchange behaviour from individual agent level decision making. Agent-based simulations hold great potential for studying emergence; the repeated interactions between individuals that lead to macrolevel behaviour. Most social exchange research has relied upon experimental research in laboratory settings. This research has been scientifically useful in that it creates an environment which is largely free of extraneous variables. The ability to simulate microlevel behaviour from the ground up has allowed the ability to study particular agent level decisions and how that has evolved through interaction into the macro level structure that we observe empirically. With the ability to quantitatively compare the results from the agent-based simulation to that of empirical data, we have been able to uncover the following: Firstly, which exchange rule human participants are relying upon the most; secondly, which exchange rules are most relied upon under each experimental condition; and thirdly, under each condition, which combination exchange rules are most fitting to the empirical data.

An overview of the results of the current research

The data in the current study were analysed using three separate analyses. Each analysis provided a particular perspective of how each simulator factor and the interactions between factors were predicting human moves. In order to arrive at a more holistic view of how accurately the model predicted human behaviour, it was necessary to discuss the results of each exchange rule with reference being drawn from all three analyses. An overview of the results of each exchange rule have been discussed below.

(Note: The random giving and proximity exchange rules both led to accuracy scores that were clustered around the expected random value. These factors were then removed from the model in order to refine and create a better predicting model, and as such they have been excluded in the current discussion.)

Ingroup-favouritism

The results from analysis 1 indicated that the simulator predicted human moves very accurately when the ingroup favouritism exchange rule was modelled. Ingroup favouritism was expected to be a good predictor of human moves as favouring ones ingroup within the minimal group paradigm is a robust and well-known outcome. The original study using the VIAPPL application did indeed find that ingroup favouritism emerges over time in a stable fashion in the group conditions (Durrheim et al., 2016). As the data used in the current study was the same data used in the VIAPPL study, it was a safe assumption that this factor would score highly.

Under analysis 2 and 3, it was found that ingroup favouritism was a high predictor of behaviour under the experimental condition of groups with unequal starting conditions, but was not a good predictor in the remaining three conditions. Ingroup favouritism was not expected to be a good predictor in the individual conditions, as group identity was not visible to the participants. A somewhat surprising finding was that ingroup favouritism was not a commonly used exchange rule in the group condition with equal starting conditions. In this condition, it appears that reciprocity was a more relied upon exchange rule. This finding illustrates the normative pressures that are evident in exchange networks. Being loyal to the ingroup is a robust phenomenon within the minimal group paradigm, yet the normative pressure to reciprocate to those who have given to you in the past was stronger. One can conclude that inequality in these experiments had an enhancing effect on ingroup favouritism. This finding is supported by a recent study by Lei and Vesely (2010) which aimed to research the effect that income inequality has on the development of ingroup favouritism. Their findings concluded that ingroup favouritism was only found within members of the wealthier group. Additionally, the participants that were poor were more trusting towards the wealthier group than towards the poor.

Reciprocity

The exchange rule of reciprocity was a very high predictor of human decision making in most of the experimental conditions. In both conditions of group and individual with equal starting conditions, reciprocity was the modelled exchange rule that best predicted human behaviour. The experimental condition of individuals with unequal starting conditions was predicted best by an equal combination of reciprocation and self-interest. This is a surprising finding as these exchange rules could be thought of as competing with each other. A possible explanation for this finding would be that a dominant norm of economic profit maximisation is constrained by the normative obligation to cooperate with those that have been helpful in the past. The self-interest norm is likely induced by the inequality of wealth between participants, which as Miller (2001) argued, is often induced by the context. This finding is an illustrative example of the conflict that can arise between exchange rules, on one side there is a clear rationality in the participants decision making, but there is an equal normative obligation to cooperate with others.

Overall, there is much support for the generic norm of reciprocity argued by Gouldner (1960), yet it is clear that contesting norms such as ingroup favouritism under a condition of inequality can supress this norm.

Self-interest

The modelled exchange rule of self-interest was a good predictor in the individual condition with unequal starting conditions. A previously discussed self-interest was the best predictor of human behaviour when paired with reciprocity. In the individual condition with equal starting conditions, self-interest did feature in eight of the top ten combinations with reciprocity being in the top two. These results seem to indicate that self-interest was normatively promoted, yet it was constrained by the stronger cooperative norm of reciprocity.

The pattern of economic rationality with competing normative considerations of cooperation have gained the attention of many economists (Festre, 2010).

Fairness

The fairness factor under analysis 1 had a mean Average Scaled Prediction of 0.76. This accuracy is higher than our expected value of 0.5 which means that the modelling of fairness is indeed predicting human behaviour.

When referring to analysis 2, the fairness factor, when weighted in all four experimental conditions, leads to a reduction in prediction accuracy. The prediction accuracy drops from 1.2 to under 1 on the arcsine transformed scale when fairness is introduced. This means that with fairness excluded, the average rank falls between position 1 and 2, and when fairness is included, the rank drops to position 4. This effect is attributable to the previously discussed problem of fairness being mathematically disadvantaged in comparison to the three other decision rules with binary outcomes.

Concluding thoughts

The ability to generate macro level phenomena from a set of simple rules and then compare these macro level outcomes to existing data from human experiments has informed us of which decision rules are most relied upon under each experimental condition.

We have also been able to observe how rules interact with each other to form these macro level outcomes. It is noted, for example, that ingroup favouritism and reciprocity share a relationship, as they are both in the top combinations in the group conditions. Durrheim et al. (2016) shed some light on this with the explanation that participants are likely to expect reciprocation to be more likely within their own group than with the outgroup. Ingroup favouritism is then elevated due to participants expecting their token allocations to be likely returned by ingroup members. The results of the current research indicate a dynamic interplay between these two factors.

Reciprocity also interacted with self-interest in the individual condition, crossed with inequality. Self-interest as noted by Miller (2001), may be induced by the context. The unequal starting conditions may have induced a pattern of self-giving, though it is also possible that select participants modelled self-giving, and this behaviour then became normative with other participants. Further simulations investigating temporal patterns of allocation behaviour may be able to uncover these trends.

The relationship between ingroup favouritism and self-interest is interesting in that the group conditions, where participants were aware of their group belonging, were less likely to engage in self-giving behaviour. The individual conditions with equal and unequal starting conditions tended to see more self-interest. These results suggest that ingroup favouritism was far stronger than self-interest under the minimal group situation.

Reflections on method

The approach to agent-based modelling in this research has been novel in that it has sought to be highly descriptive which is very different from the “keep it simple stupid” approach. The KISS principle is highly favoured due to the inherent problem with agent-based models that become too complicated with too many rules. When a model has too many rules, it can become very difficult to gain any meaningful results from the data. The method demonstrated in the current research quantitatively compares the simulated data to that of the human data. This comparison then allows researchers to abandon the KISS principle in favour of models that can become highly descriptive. The ability to refine a model through a sensitivity analysis, that is to add or remove factors based on the comparison with empirical data, allows researchers the ability to test theory (Thiele, Kurth, & Grimm, 2014).

Limitations and areas for future research

A limitation in the current research that could be addressed in future research is the way in which fairness is modelled. As mentioned in the methods chapter, a smaller scale of measurement was inadvertently introduced when fairness was completely excluded from the final Empathy Matrix. This meant that comparisons between simulations that included fairness and ones that did not were misleading. For publication, this limitation will be overcome by simply changing the weightings of the simulated exchange rules. In the current study, the rules were weighted at three levels with increments of 50. This resulted in each exchange rule being weighted at 0, 50 or 100. When weighted at 0, the exchange rule was mathematically cancelled out entirely. The proposed weightings of 1, 50 and 99 will overcome the problem of scale by ensuring that no simulated exchange rule will be fully excluded from the final Empathy Matrix.

A second limitation in this study would be that the analysis did not include a temporal aspect which would allow the observation of norms emerging over time. The current research has modelled behaviour from interpersonal interactions and has compared the macrolevel outcomes of the simulation to empirical data. Future research could adapt the analysis to uncover changes in exchange behaviour over time.

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Appendices

Appendix 1: Multilevel model results table

Fixed effects:	Coef.	Std. Err.	Df	T-value	P-value
(Intercept)	1.302379	0.015274	17.248258	85.268	< 0.0000000000000002 ***
Individual.Group1	0.001414	0.021601	17.248258	0.065	0.94855
Equality.Inequality1	-0.050938	0.021601	17.248258	-2.358	0.03041 *
Reciprocity.weight50	-0.015140	0.002404	51184.000002	-6.297	0.000000000306 ***
Reciprocity.weight100	-0.012546	0.002404	51184.000013	-5.218	0.000000181663 ***
self.Interest.weight50	-0.043379	0.002404	51184.000015	-18.042	< 0.0000000000000002 ***
self.Interest.weight100	-0.042554	0.002404	51184.000016	-17.698	< 0.0000000000000002 ***
Group.Weight50	-0.104499	0.002404	51184.000011	-43.462	< 0.0000000000000002 ***
Group.Weight100	-0.123138	0.002404	51184.000017	-51.214	< 0.0000000000000002 ***
Fairness.weight50	-0.354670	0.002404	51184.000016	-147.509	< 0.0000000000000002 ***
Fairness.weight100	-0.340735	0.002404	51184.000017	-141.714	< 0.0000000000000002 ***
Individual.Group1:Equality.Inequality1	-0.056826	0.030548	17.248257	-1.860	0.07999 .
Individual.Group1:Reciprocity.weight50	0.001715	0.003400	51184.000017	0.504	0.61405
Individual.Group1:Reciprocity.weight100	0.006751	0.003400	51184.000029	1.985	0.04710 *
Equality.Inequality1:Reciprocity.weight50	0.019200	0.003400	51184.000017	5.647	0.000000016446 ***
Equality.Inequality1:Reciprocity.weight100	0.021468	0.003400	51184.000029	6.314	0.000000000275 ***
Individual.Group1:self.Interest.weight50	-0.045480	0.003400	51184.000030	-13.375	< 0.0000000000000002 ***
Individual.Group1:self.Interest.weight100	-0.056424	0.003400	51184.000029	-16.594	< 0.0000000000000002 ***
Equality.Inequality1:self.Interest.weight50	0.055590	0.003400	51184.000030	16.349	< 0.0000000000000002 ***
Equality.Inequality1:self.Interest.weight100	0.061148	0.003400	51184.000029	17.983	< 0.0000000000000002 ***
Individual.Group1:Group.Weight50	0.068666	0.003400	51184.000027	20.194	< 0.0000000000000002 ***
Individual.Group1:Group.Weight100	0.079751	0.003400	51184.000032	23.454	< 0.0000000000000002 ***
Equality.Inequality1:Group.Weight50	0.067243	0.003400	51184.000027	19.775	< 0.0000000000000002 ***
Equality.Inequality1:Group.Weight100	0.058744	0.003400	51184.000032	17.276	< 0.0000000000000002 ***

Individual.Group1:Fairness.weight50	0.109053	0.003400	51184.000033	32.071	< 0.0000000000000002 ***
Individual.Group1:Fairness.weight100	0.103666	0.003400	51184.000033	30.487	< 0.0000000000000002 ***
Equality.Inequality1:Fairness.weight50	0.008358	0.003400	51184.000033	2.458	0.01397 *
Equality.Inequality1:Fairness.weight100	0.010294	0.003400	51184.000034	3.027	0.00247 **
Individual.Group1:Equality.Inequality1:Reciprocity.weight50	-0.007738	0.004809	51184.000025	-1.609	0.10760
Individual.Group1:Equality.Inequality1:Reciprocity.weight100	-0.020237	0.004809	51184.000036	-4.208	0.000025769401 ***
Individual.Group1:Equality.Inequality1:self.Interest.weight50	0.013091	0.004809	51184.000037	2.722	0.00648 **
Individual.Group1:Equality.Inequality1:self.Interest.weight100	0.013372	0.004809	51184.000036	2.781	0.00542 **
Individual.Group1:Equality.Inequality1:Group.Weight50	0.022744	0.004809	51184.000033	4.730	0.000002255046 ***
Individual.Group1:Equality.Inequality1:Group.Weight100	0.050635	0.004809	51184.000038	10.530	< 0.0000000000000002 ***
Individual.Group1:Equality.Inequality1:Fairness.weight50	-0.176080	0.004809	51184.000040	-36.616	< 0.0000000000000002 ***
Individual.Group1:Equality.Inequality1:Fairness.weight100	-0.191347	0.004809	51184.000039	-39.791	< 0.0000000000000002 ***

Note. *p<0.1; **p<0.05; ***p<0.01

Appendix 2 Ethical clearance certificate

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YAKWAZULU-NATALI

12 May 2014

Mr James Terence Edward Theil (210552448)
School of Applied Human Sciences – Psychology
Pietermaritzburg Campus

Dear Mr Theil,

Protocol Reference Number: HSS/0359/014M
Project Title: The simulation of social exchange: Developing a multidimensional model to mimic human interaction

Full Approval – No Risk

In response to your application dated 23 April 2014, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol have been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for a period of 3 years from the date of issue. Thereafter Recertification must be applied for on an annual basis.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

....

Dr Shenuka Singh (Chair)

/ms

cc Supervisor: Professor Kevin Durrheim
cc Academic Leader Research: Professor D McCracken
cc School Administrator: Mr Sabonelo Gumede

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