Modelling the effects of information gathering on social decision making

Damon Hayhurst

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I confirm that this write up is my own work and does not involve

plagiarism as defined in the module information provided

Signed and dated

This is the abstract

Are decisions made in our own self-interest influenced by the manner in which we form our conclusions? Previous work in the study of decision making has shown that the way in which we gather information can influence the final outcome. In a social setting, self interested and other facing motives have been shown to have their value tracked independently by specific neural circuitry. Using mouse tracking data from a similar experiment we ask whether the manner in which we gather information can predict which one of these motives we are likely to pursue.

Aims

The aims of this study is to gain an insight into how the effects of information gathering influence our decision making in a pro-social context. Using process tracing, we hope to observe and characterise strategies that are used in order to arrive at these decisions. Such an approach hopes to shed light further on the processes that underlie decision making in human behaviour.

Objectives

- Determine if information gathering strategy in social decision making reflects an individual preference

- Understand whether perceived monetary outcomes to self and another have an affect on the way we gather information

- Ask whether information gathering strategy can be used a predictor in social decision making

Background

Understanding decision making in humans

Present day understanding of decision making in humans takes it's inspiration from Herbert A Simon's approach of Bounded Rationality. Where prior understanding suggested that human beings act as rational agents always seeking to maximise self interest, Bounded

Rationality suggested that humans capability to act in a perfectly rational manner was constrained by internal and external factors.

Bounded Rationality places as much of an emphasis on the processing of information during the decision making as the decision itself. Pivotal to the concept, it was suggested that human's mental capacity to make choices is subject to heuristics or mental simplifications that contend with it's ability to be a perfectly rational agent but aid it's ability to make decisions in the face of increasing complexity (Payne, 1976). Simon outlined Satisficing as a key mechanism employed in the face of decisional complexity. Such a model of process attempts to define the appropriate option amongst choices as being the first option to surpass pre conceived threshhold. Rather than cope with the cognitive overhead of comparing every option against all of the others in a perfectly rational manner, humans will opt for the first choice that is deemed sufficient and satisfactory (Simon, 1955,1956). Early work into the mechanisms that perpetrate the notion of Bounded Rationality revealed the necessity for capturing process data. The Priority Heuristic attempted to explain choices within the context of simple monetary gambles using an ordered list of criteria. While the mechanism was shown to be significant at the aggregate level, the model failed to capture differences at the individual level. Further research into the manifestation of the Priority Heuristic, using process data, uncovered that in actual fact the underlying process did not mimic the priority ordering set out by the heuristic. The data, however, revealed that choice could be predicted significantly by the number of transitions into and out of a choice. The uncovering of such mechanisms highlights the need for processing data in explaining how humans make decisions. Process data can provide the explanatory power for decision making differences and inform the development of heuristics that can be applied at the individual level (Brandstätter et al., 2006), (Willemsen and Johnson, 2011).

Decision making as a cognitive process

The deliberation between two option does not represent two discrete states in cognition. Mental activity occurs throughout the decision making process. In this sense, cognition is

best viewed as a continuous system with a set of intermediary states representing a graded
spectrum between both options. The two classifications acting as attractor basins for which
the decision making process finally rests in (Spivey and Dale, 2006).

Capturing the decision making process

Process tracing is a methodology used to gain insight into the decision-making process by
extracting data that reveals the underlying cognitive mechanisms. This involves various
techniques, ranging from simple verbal protocol analysis, where participants articulate their
thoughts aloud, to advanced methods like neural tracing using MRI machines (Ford et al.,
1989). The goal of these methods is to capture detailed data from different stages of the
decision-making process and use that information to inform and develop process models.
Studying decision-making involves analysing different stages, such as problem
identification, information gathering and decision selection. Each stage requires specific
methods of data extraction to effectively capture the nuances of decision-making. For
instance, in the information gathering stage, researchers might employ eye-tracking to see
where attention is focused, or they might use tools like MouseLabWeb to observe how
individuals search for and process information. The choice of instrumentation is crucial, as
insights into decision making are limited by the resolution and representation of the output
data. Efforts must be made to consolidate these representations with process models in
order to enhance their development and applicability.

MouseLabWeb

MouseLabWeb (and offline counterpart, MouseLab) is one such development in process
tracing that fosters an environment fit for observing the information gathering stage in
decision making. Utilising the dynamic properties of Javascript in the context of a web
page, MouseLabWeb describes an interactive framework that tracks users' attentional focus
on decision-making elements as they engage with different options. MouseLabWeb
experiments consist of a browser page containing adjacent pairs of hidden view boxes. Each
pair represents an option and the make up of each pair is a box containing a piece of

information relevant to that particular option. Positioning the mouse cursor over one of
these boxes reveals the concealed information. The mouse cursor movements are tracked
and then stored on a trial by trial basis. Such data can be used to observe where a
participant's focus lies. The simplistic design of a MouseLab experiment reduces the
cognitive load on the participant, affording them simple cursor movements instead of
lookup to memory ("Mouselab WEB," n.d.).

Interpreting information gathering data

Interpreting results from a MouseLab experiment involves discerning attributional qualities
from a given trace. Costa-Gomes et al. define two events in a process trace that can
provide insight into the underlying characteristics of a trace. Occurrence, being that a
particular piece of information has occurred within a process trace and therefore, that piece
of information can be considered as part of the overall strategy underlying the trace. An
absence of an occurrence of a particular piece of information suggests a strategy that is
made without considering the full picture and could be conceived as impulsive. And
Adjacency, if two adjacent pieces of information occur sequentially within a trace then it
means a comparison has likely to have taken place. An absence of adjacency could
represent a disregard for certain aspects underlying the decision such as in social preference
based choices, where the adjacent pairs show to be payoffs related to you or the other
participant. An absence of adjacency in this case suggests motives that are wholly self
concerned. The decisional lookups and their contextual information can together help
attach a type to a specific process trace (Costa-Gomes et al., 2001).

Reeck et al. found success through observing both the acquisition of information and the
duration within which they looked at said pieces of information. Using the Intertemporal
Choice task as options in the MouseLab experiment, they were able to disseminate two
underlying search strategies and showed success in linking their use to the decisional
outcome. Using K-means clustering, two types of strategy emerged. Comparative
searchers, who exhibited a more patient approach involving large proportions of adjacency

and integrative searchers who showed fewer occurrences of each piece of information and
shorter durations of observation in their process trace before deciding. Success was found
in observing that comparative searchers were significantly more likely to pick the more
patent option in the Intertemporal choice task (Reeck et al., 2017).

The neurobiology of social decision making

Evidence suggests that neural circuitry involved in social decision making does not
distinguish itself from that of the circuitry involved in other forms of decision making.
Value based processing found in ventromedial prefrontal cortex (vmPFC) supposedly
integrates signals from other areas of the brain during the decision making process, feeding
signals back based on value representation change. This understanding, known as the
extended common currency schema, directly contrasts prior theories that suggested our
social decision making skills evolved as part of a separate adaptive system (Ruff and Fehr,
2014).

The specificity in social decision making comes from the neural circuits that the vmPFC
tracks during social dilemma is faced. The lateral prefrontal cortex (LPFC) which tracks
value to self and the right temporoparietal junction (rTPJ) which tracks value to others. It
was suggested that these two circuits were involved in the social decision making process
within a study that used the Message Game (further elaborated upon in the Methods
section) as it's stimuli. Using neuroimaging technology, Shuster and Levy observed the two
neural circuits independently tracking their respective motives by modifying trial
parameters specific to the Message game that altered the perceived social outcomes. The
vmPFC representing the value computation between the two varied on an individual level
(Shuster and Levy, 2020).

Methods

A secondary analysis was carried out from the results of pre existing experiment. The
primary stimuli, of which, was a variation of The Message Game that was carried out
within a MouseLabWeb environment.

The Message Game

The Message Game is a form of experimental game that models a particular complexity
faced by individuals in pro-social environments. The game uses honesty to illustrate how
decision making can be affected by value judgements that pit our own self interest against
our altruistic sensitivities. The game involves two roles. The Sender and the Receiver. The
Sender must send a message to the Receiver informing them of a particular box to open
from a choice of four. Each of the boxes contains differing amounts of money for the
Sender and the Receiver should that box be chosen. The Sender can ultimately see what's
inside each of the boxes in terms of how much money they will receive versus the amount
that the Receiver will. Only the Receiver opens the box, however. A message is sent by the
Sender to the Receiver with words to the affect of 'Box X is best for you'. The dishonesty
comes from the Sender being able to suggest a box that might not necessarily represent the
truth and instead picking a box that contains a larger amount of money for themselves and
less money for the Receiver. With the Receiver unable to see the quantity of money they
potentially missed, they must decide whether to trust the Sender's recommendation and
open the suggested box.

Experimental Variation

In this variation, focus is placed entirely on the Sender. Two of the boxes are blank
meaning that the Receiver has no choice but to pick the Sender's recommendation or risk a
2 in 3 chance of getting no monetary income. The participant plays as the Sender for the
majority, however, does get to have a go at playing at the Receiver role only to understand
the dilemma faced. The participant then spends 80 trials in the Sender role where the
process data is tracked. The position of the monetary rewards in the boxes are then altered
on a trial by trial basis so that decisions are encouraged to be deliberate and do not
succumb to laziness.

The values held in each of the two boxes vary on a trial by trial basis. Each of the two
boxes consists of two values representing a profit for the Sender and Receiver. These boxes

always contain differing amounts for the Receiver and Sender. The box with the higher

amount for the Receiver, if chosen, represents the Sender telling the truth to the Receiver.

Likewise, the box with the lower amount represents the Sender making a dishonest claim to
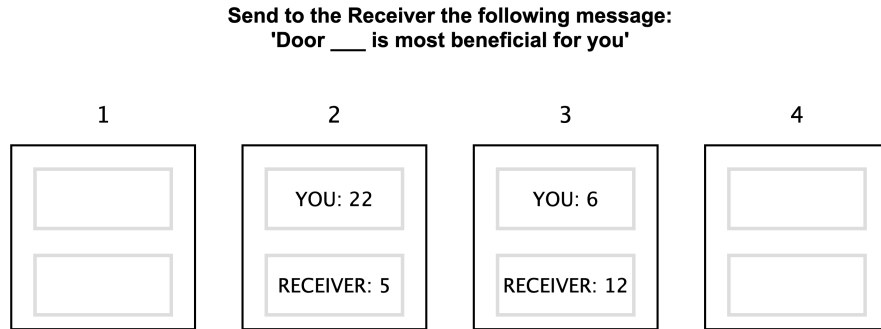
the Receiver.

Send to the Receiver the following message:
'Door ___ is most beneficial for you'

1	2	3	4
	YOU: 22	YOU: 6	
	RECEIVER: 5	RECEIVER: 12	

Figure 1

Layout of boxes and AOIs for one specific trial. Door 2 represents the Sender choosing to

lie. Door 3 represents the truth. The 2 AOIs inside door 2 are SELF LIE (top) and

OTHER LIE (bottom). Door 3 hold the AOIs, SELF TRUE (top) and OTHER TRUTH

(bottom).

Being that the trials were carried out in a MouseLabWeb environment, the amounts

contained within the boxes shall be referred to as Areas of Interest (AOIs). The AOI

representing what amount the Sender receives for the truth telling box is SELF TRUE and

the one representing the amount for the Receiver is OTHER TRUTH. AOIs corresponding

to the amounts for the dishonest box are SELF LIE for what the Sender receives and

OTHER LIE for the receiver. Theses AOIs are the pieces of information hidden from view

that can only be revealed by hovering a mouse cursor over the panel. Horizontally adjacent

lookups correspond to comparisons of amount awarded to one particular role and vertical

adjacency compares values awarded for both roles for a given option. The vertical order of

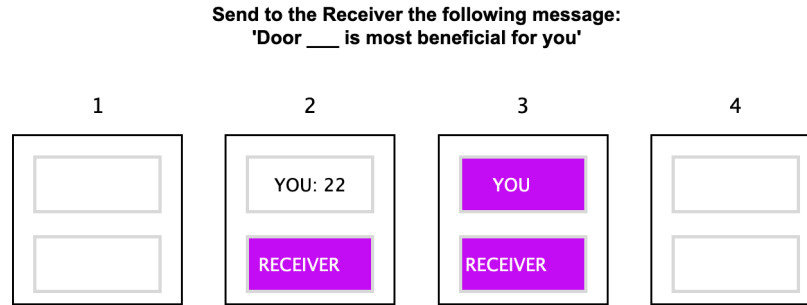the AOIs swaps as well in order to encourage deliberate observations.

Figure 2

What the participant sees during experimental trials. The top AOI of door 2 is currently being hovered over with the mouse.

With the values and positioning of each AOI altering on a trial basis, one can gain an insight into the process and circumstances that inhibit a participant from acting in a rational manner. The game theoretic viewpoint suggests that the Sender should always choose to act in their own self interest by picking the option that represents the maximum utility to themselves ie. the box with the most value to them. Ultimately there are no repercussions for lying and therefore rational agents only need to seek value from profit. Using human participants and recording process data, we can observe when a humans' s show aversion to self interest and their altruistic sensitivities take over.

Procedure

Results for the experiment carried using the primary stimuli, the variation of the the Message game, recorded a collective total of 89 participants. Rows represented a single trial for each participant. The rows provided information such as the values that were in each AOI, the selected box number, reaction time and a process trace.

Since trial order was randomised, an index number was assigned to each trial. That number was based upon every unique set of values contained within the AOIs. Trials that shared the same amounts were assigned the same index value. See Figure 9 and 10. The trials could then be aggregated across participants based on the profits and losses earned

by the Sender and Receiver per trial.

The trials were then grouped per participant and were assessed under a set of criteria that
might warrant their exclusion. A breakdown of these can be found in the Results section.
Each remaining trial had a process trace consisting of a semi-colon delimited set of
timestamps and coordinates representing the position of the mouse cursor at any given
time during the trial. By corroborating this information with the stated participants screen
width and the per trial position of each box and containing values, it could be calculated
whether a particular timestamp represented a cursor position that was inside one of the
four AOIs. From this, a timeline could be built showing durational occurrences of any of
the four AOIs within the process trace.

Average Analysis

Using the newly created timeline, the average dwell for each of the four AOIs was
calculated per trial. Along with the number of transitions between adjacent AOIs per trial.

Cluster Analysis

The timelines were assessed under a further notion of similarity. By taking into account a
point by point comparison between each of the timelines on the millisecond level,
underlying trends can be uncovered that forgo the detection of average calculation. The
consolidation of such point data provides the affordance of perceiving time series similarity
under a single distance measure. This output can then be used to inform the formation of
clusters and classification.

Dynamic Time Warping

Dynamic Time Warping (DTW) is a length-invariant measure of distance between two
time series. It takes the minimum cost alignment between two sequences using a one to
many comparison of each point. Where the Euclidean measure only takes into account a
point to point mapping using equal length time series, the DTW measure doesn't abide by
such strictness in it's comparison. Using a many to many approach means that a DTW
measure can factor in patterns of activity that are approximate both series and realise

they're similarity. In this way, DTW can perceive relationships in time series that are shifted and subject to noise.

A pairwise comparison was drawn between each individual trial for each participant using DTW as a measure of similarity. Each trial's timeline was represented in a n x 4 array where n was the quantity of milliseconds in the trial and 4 elements representing the binary state of each AOI describing whether the cursor was within it's bounds or not. Prior to comparison, each time series was subject to z normalisation. Thus, ensuring that greater variation in longer length series was accounted for and comparison could focus on the shape of the data.

Clustering

Hierarchical clustering was then used with the calculated DTW metric to achieve a desired number of clusters. The clustering mechanism used in this instance, Agglomerative, recursively merges clusters using a bottom up approach. Each cluster represents a single trial at the beginning and then trials are merged based on the comparison that represents the smallest distance. Clusters are then recursively merged with a cluster's proximity to another cluster being defined by the maximum distance that can be described based on the cluster's constituent trials. The process repeats until the number of desired clusters is reached.

In the analysis, the desired number of clusters was defined as the number that returned the highest value from the pseudo F statistic. The statistic identifies well-fitting clusters by maximising between-cluster variance while minimising within-cluster variance. By evaluating this measure up to 20 clusters, the resulting clusters were expected to represent a level of classification that avoids overfitting.

Results/Findings

Trial and Participant Quantities

The processing of data removed a proportion based on criteria that represented a lack of engagement with the experiment. six participants were removed for not finishing it. 20

were removed for telling the truth over 95% the time and a further 14 participants were removed for recommending the blank boxes to the receiver in over five percent of the trials. Interestingly, no participants were removed for lying over 95% of the time; despite this being the approach favoured in game theory. A further 40 trials were removed from the dataset because they recorded decision making times that were three standard deviations away from the mean. An approach also taken by Reeck et al., suggesting a similar lack of engagement with the task at hand.

Irregularities and missing data that represented a failure in process tracing were also removed from the dataset. 10 participants were removed for having not recorded mouse coordinates in over 85% of their trials and a further 108 trials removed from the remaining valid set because of similar lack of mouse coordinates. Irregularities in some of the coordinate data meant that AOIs could not identified through measurement. 42 trials were removed because of this and one participant also, that failed to record screen width data. If such impairments in the dataset had been included by merely estimating their missing qualities, it would have compromised the overall integrity. Omitting them highlights the essential role of accurate process tracing.

In further regards to accurate process tracing, some consideration was taken towards events that lasted under a threshold of 200ms. This process accounts for jittery movements by the participant and periods of dwell that do not amount to the recognised minimum for reading hidden text in object recognition (DiCarlo et al., 2012) and MouseLab literature (Willemsen and Johnson, 2011). Once all events in each trial accounted for this threshold, a further 103 trials were removed from the total citing an absence of any remaining valid dwell events within AOIs.

After accounting for engagement criteria and irregularities, the number of valid trials was recorded for each participant and a further six participants were excluded from the analysis. The number of valid trials for each of these participants represented a quantity that was less than three quarters of the intended 80 trials for each participant. Given, the

ordering of each trial was randomised, the set of valid trials for each of these participants could represent biases in likelihood to lie relative to the whole data set.

From the original pool of 89 participants, only 32 remained after all removals. An overall data set that contained 2489 trial instances each with a valid process trace.
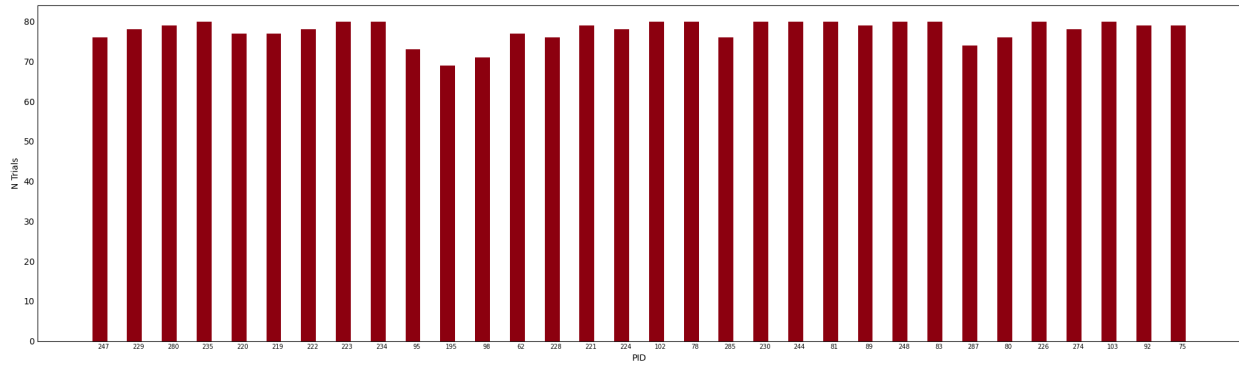

Figure 3

Bar graph representing number of trials in the final valid data set for each participant.

Descriptives

Lie Percentage

Across trials the propensity to lie displayed a high degree of variance. The average likelihood to lie on any given trial was 38% ($N = 2489$). Across participants, the propensity to lie was measured with a 22% (Q1) - 51% (Q3) interquartile range for a given individual. Across instances of unique trial, where unique is defined by the specific quantities pertained to in the boxes, the range was 0 - 90% with an interquartile range of 16% (Q1) - 59% (Q3) for any given trial.
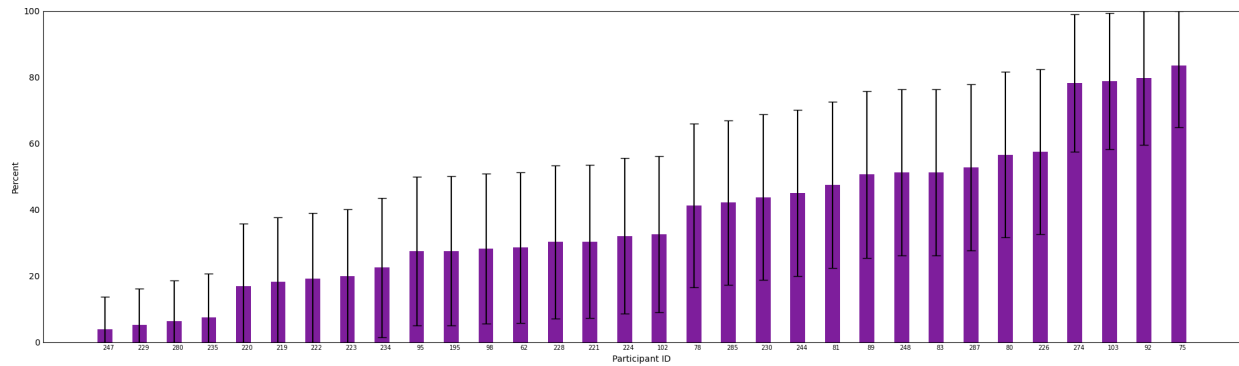
Figure 4

Bar graph representing the percentage amount of lies across participants
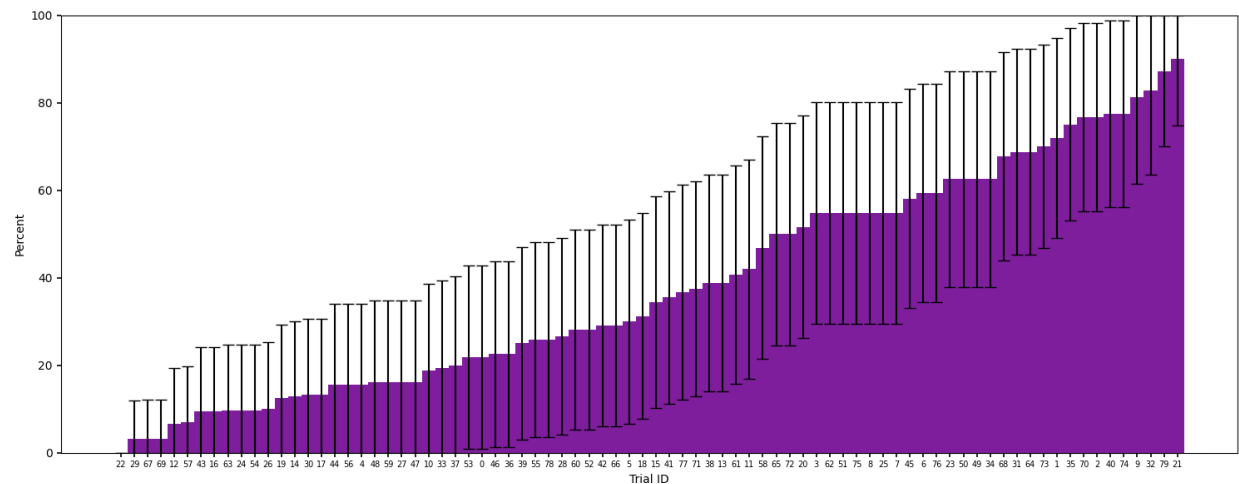
Figure 5

Bar graph showing the percentage of lies for each trial condition.

Dwell Time Distribution

Reaction time (or the time it takes to make a decision) showed a large amount of range. The average reaction time was 6513 ms ($SD = 3050$ms) with an interquartile range of 4393 (Q1) - 7871 ms (Q3).
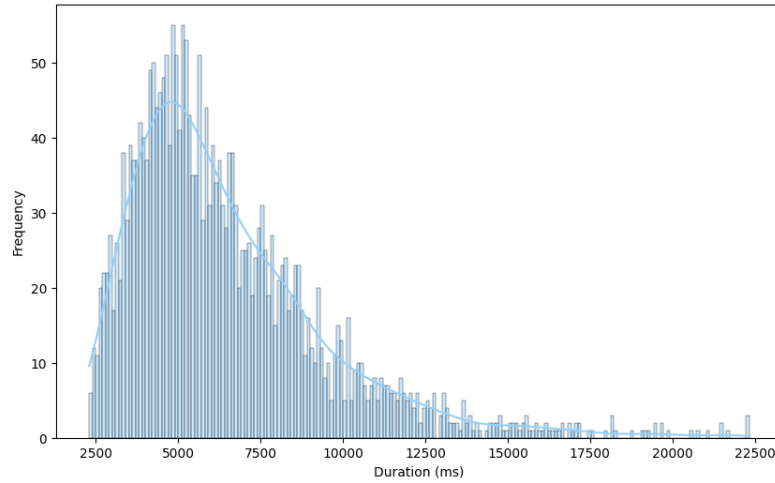
Figure 6

Distribution of reaction time ie. time taken to make a decision.

The amount of spent dwelling on one of the four AOIs on the screen was considered. The AOIs, SELF LIE ($M = 470$ms, $SD = 428$ms), SELF TRUE ($M = 420$ms, $SD = 343$ms), OTHER LIE ($M = 571$ms, $SD = 423$ms) and OTHER TRUTH ($M = 604$ms, $SD = 472$ms) all recorded means within 150ms of one another. A large proportion of the trials reported no dwell time for at least one of the given AOIs. Both SELF TRUE and SELF LIE were absent from the dwell timelines of 450 trials, representing an omission rate of 18%. OTHER TRUE and OTHER LIE were omitted from 221 and 240 respectively representing around 10% each, of all trials.

Figure 7

Distribution of average dwell time for each AOI. The distribution only accounts for average dwell time of each AOI that were under 1000ms. Each AOI also had a proportion of average dwell times that were 0, which were also omitted.
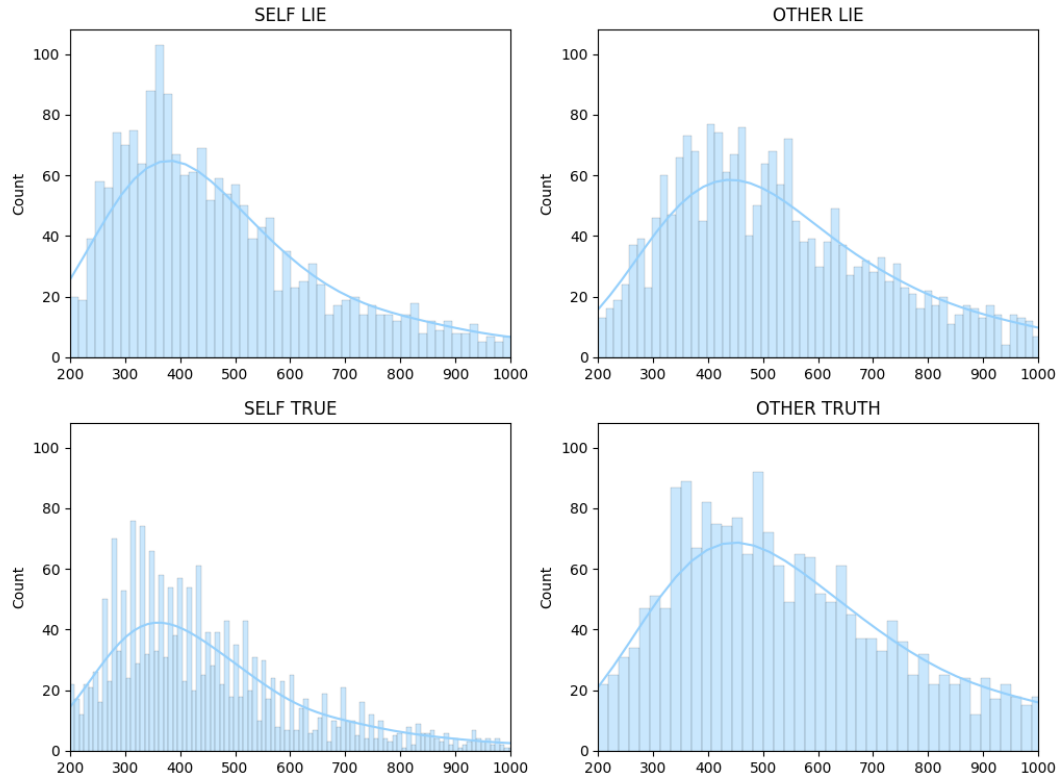
Figure 8

Distribution of number of transitions between AOIs across trials.
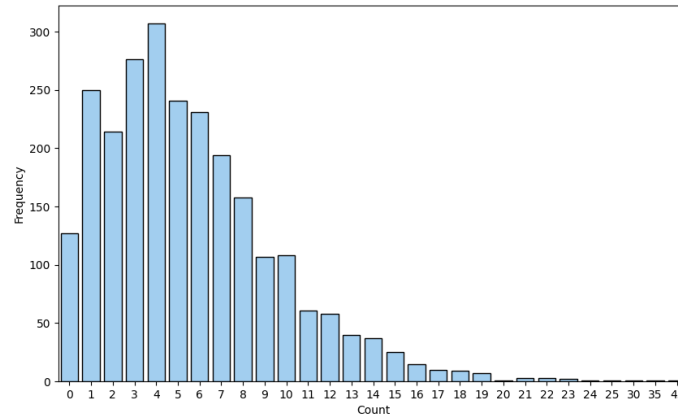
The number of transitions is marked by where a participant would move the cursor from
one AOI to another was also observed across all trials. The mean number of transitions
between AOIs was ($M = 5.6$, $SD = 4.1$) with an interquartile range of 3 (Q1) - 8 (Q3).

Task Condition Analysis

Lie Percentage
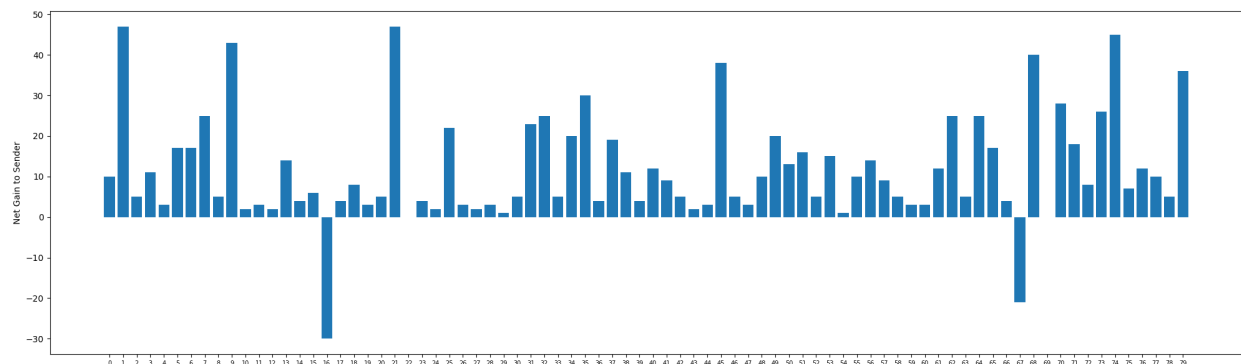
Figure 9

*Bar chart showing the amount gained by the Sender should they choose to lie in the
corresponding trial.*

Each of the trials involved giving differing amounts to the sender and the receiver based on whether the sender decided to lie or not. The average net gain to the sender was 12 $(SD = 13)$ per trial. The median was 8 and had an interquartile range of 4 (Q1) - 17 (Q3). The average loss to the receiver was 11 $(SD = 9)$ with a median of 8 and an interquartile range of 4 (Q1) - 15 (Q3).

Figure 10

Bar chart showing the amount lost by the Receiver should the Sender choose to lie in the corresponding trial.
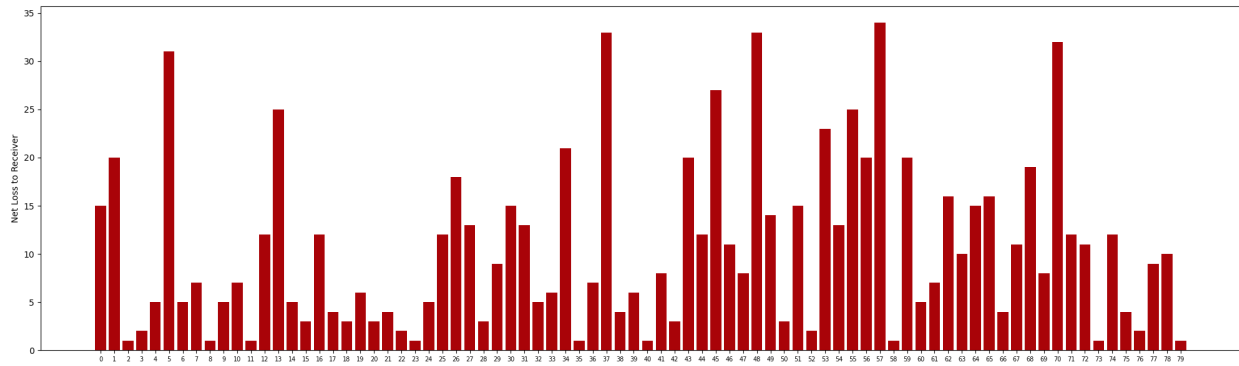
The percentage of senders that chose to lie in the experiment increased as the net gain to the sender did. Senders lied the least when they incurred a net loss by lying. Only lying 6% $(N = 63)$ of the time. From net gains below 10 to above 10 the percentage who chose to lie increased, from 24% $(N = 1336)$ to 55% $(N = 1153)$. When gains were above 20, the percentage who chose to lie in this task scenario grew to 70% $(N = 560)$ and when they were above 30 the amount who decided to lie showed further increase but to a lesser extent 76% $(N = 250)$.
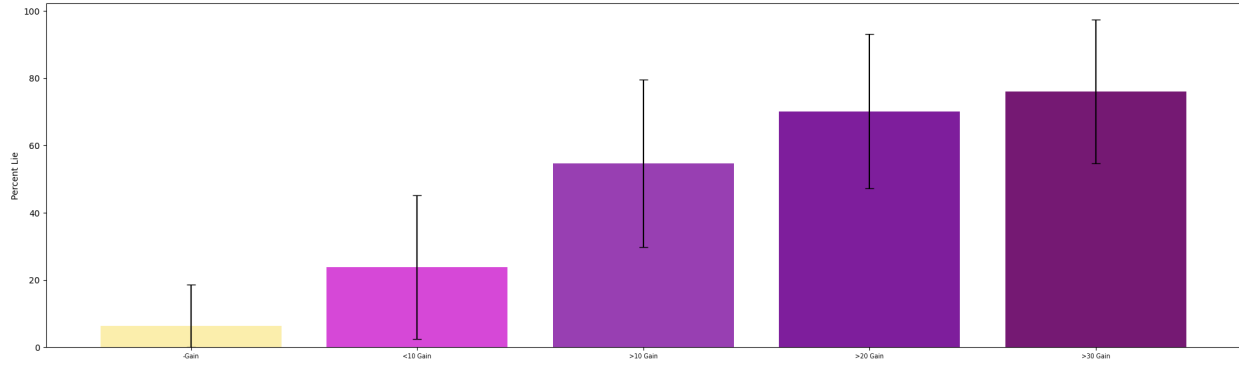
Figure 11

Percentage who chose to lie based on the amount gained by lying.

A significant difference in the proportion of lies was observed across trials where the sender gained less than 10 and when they received more than 10, $\chi^2(1, N = 2489) = 248$, $p < .001$. A significant difference was also observed across trials where gain was under 30 and over 30 $\chi^2(1, N = 2489) = 167$, $p < .001$.
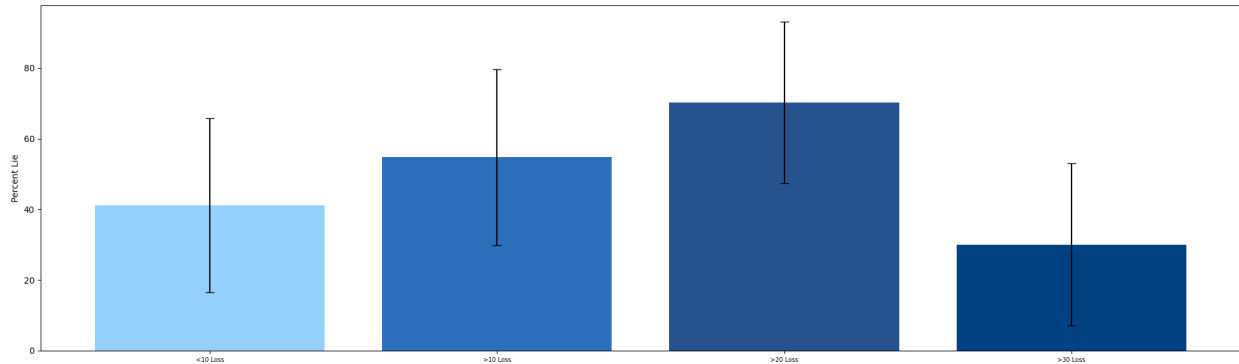

Figure 12

Percentage of senders who chose to lie based on how much the receiver would lose.

Senders were less likely to lie when the losses to the receiver were great. When losses were under 10, 41% ($N = 1340$) of senders chose to lie. With losses greater than 10, 55% ($N = 1153$) chose to lie through to losses greater than 20 where the percentage of senders who chose to lie showed a notable increase, to 70% ($N = 560$). When losses to the receiver were larger than thirty the amount of senders was 30% ($N = 150$)

The difference in lie percentage between trials where losses to the receiver were over 10 and
trials where losses to the receiver were under 10 was shown to be significant $\chi^2(1,
N = 2027) = 45$, $p < .001$ as well as in trials where losses to the receiver were over and
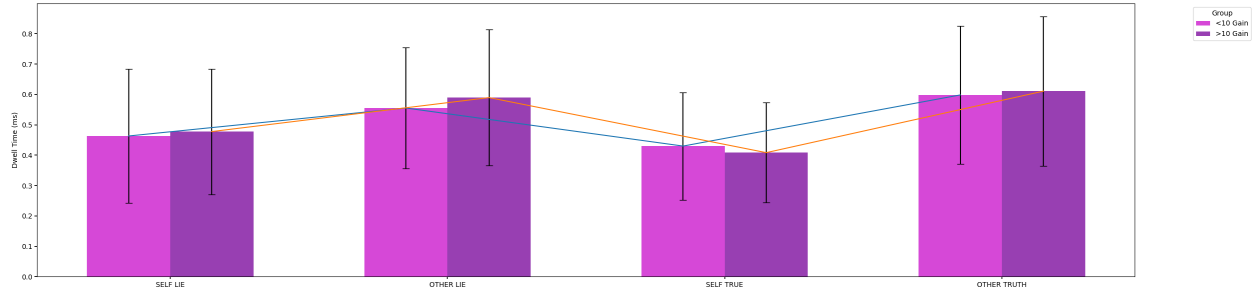under 30 $\chi^2(1, N = 2489) = 4.2$, $p = .042$.

Dwell Time

Figure 13

*Average Dwell Time for each AOI comparison between trials where net gain to the Sender
was less than 10 and trials where the net gain was more than 10*

	<10 Gain to Sender		>10 Gain to Sender		T-test result	
	M (ms)	SD (ms)	M (ms)	SD (ms)	$t(2487)$	p
SELF LIE	463	441	478	413	0.84	.798
SELF TRUE	430	354	408	329	-1.6	.460
OTHER LIE	555	398	590	448	2.0	.173
OTHER TRUTH	598	455	611	492	0.66	.511

Table 1

*Comparison of mean and standard deviation of dwell times for each AOI across trials
where the net gain to Sender was less than 10 versus trials where the net gain was more
than 10. (FDR Corrected)*

Table 1 shows that there was an no significant difference between the average dwell time of
the four AOIs across trials where the net gain to the Sender was less than 10 versus when
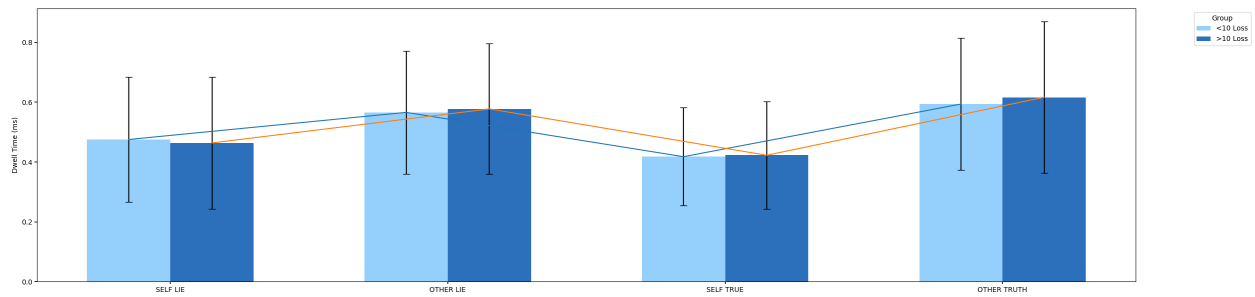
it was more than 10.

Figure 14

Average Dwell Time for each AOI comparison between trials where net loss to the Receiver

was less than 10 and trials where the net loss was more than 10

	<10 Loss to Receiver		>10 Loss to Receiver		T-test result	
	M (ms)	SD (ms)	M (ms)	SD (ms)	$t(2491)$	p
SELF LIE	475	417	478	413	0.15	.880
SELF TRUE	418	328	408	329	-0.71	.476
OTHER LIE	566	410	590	448	1.4	.224
OTHER TRUTH	594	441	611	492	0.92	.511

Table 2

Comparison of mean and standard deviation of dwell times for each AOI across trials

where the net loss to the Receiver was less than 10 versus trials where the net loss to the

Receiver was more than 10. (FDR Corrected)

Similarly, in Table 2, there was no significant difference between the dwell times in trials

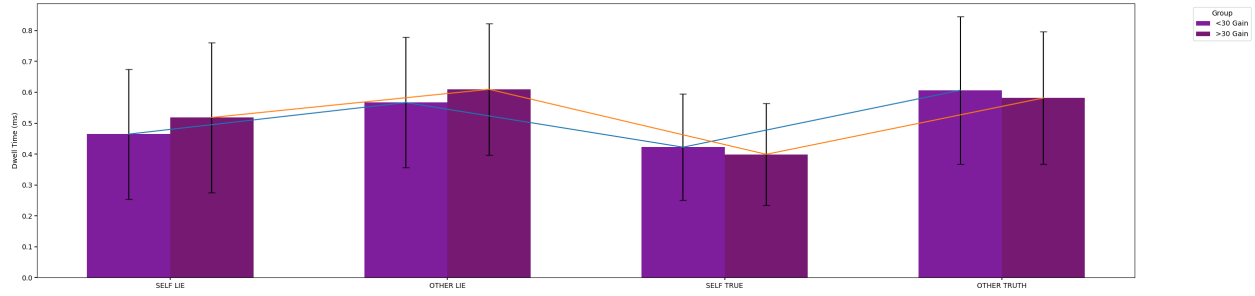where the loss to the Receiver was above 10 versus trials where it was below 10.

Figure 15

Average Dwell Time for each AOI comparison between trials where net gain to the Sender was less than 30 and trials where the net gain was more than 30

	<30 Gain to Sender		>30 Gain to Sender		T-test result	
	M (ms)	SD (ms)	M (ms)	SD (ms)	$t(2487)$	p
SELF LIE	519	486	465	421	-1.9	.235
SELF TRUE	399	329	422	345	1.0	.476
OTHER LIE	610	424	567	422	-1.5	.224
OTHER TRUTH	582	428	607	477	0.79	.511

Table 3

Comparison of mean and standard deviation of dwell times for each AOI across trials where the net gain to the Sender was less than 30 versus trials where the net gain was more than 30. (FDR Corrected)

Across trials where the net gain to Sender and the net loss to the Receiver was at larger quantities there was found to be no significant difference in dwell times as seen in Table 3 and 4.
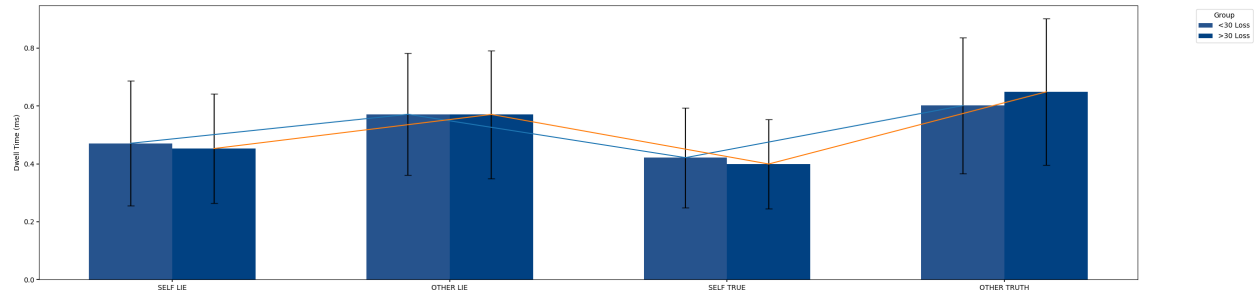
Figure 16

Average Dwell Time for each AOI comparison between trials where net loss to the Receiver was less than 30 and trials where the net loss was more than 30

	<30 Loss to Receiver		>30 Loss to Receiver		T-test result	
	M (ms)	SD (ms)	M (ms)	SD (ms)	$t(2487)$	p
SELF LIE	471	431	453	379	0.51	.817
SELF TRUE	421	345	399	307	0.76	.476
OTHER LIE	571	421	571	422	0.01	.990
OTHER TRUTH	601	470	649	507	-1.2	.511

Table 4

Comparison of mean and standard deviation of dwell times for each AOI across trials where the net gain to the Sender was less than 30 versus trials where the net gain was more than 30. (FDR Corrected)
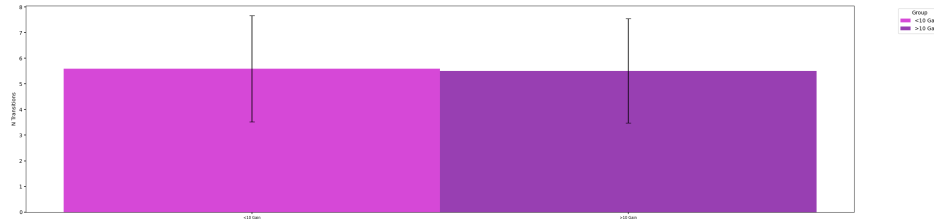
Number of Transitions

Figure 17

Comparison of average number of transitions between trials where the net gain to the

Sender was less than 10 and trials where the net gain was more than 10

The difference in number of transitions proved not to be significant when comparing trials

where the net gain to the Sender is above ($M = 5.5\%$, $SD = 4.1\%$) or below 10

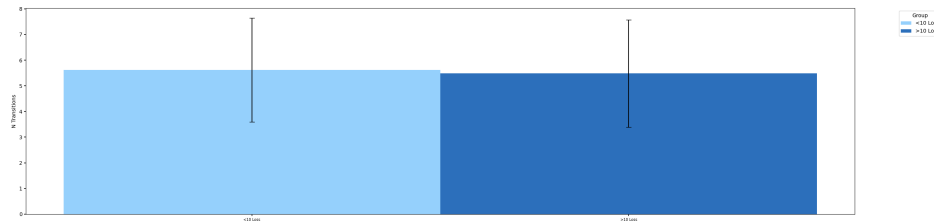($M = 5.6\%$, $SD = 4.1\%$), $t(2487) = -0.5$, $p = .617$.

Figure 18

Comparison of average number of transitions between trials where net loss to the Receiver

was less than 10 and trials where the net loss was more than 10

Similarly the difference in number of transitions showed to be insignificant when comparing

trials where the Receiver made a loss of above ($M = 5.5\%$, $SD = 4.1\%$) or below 10

($M = 5.6\%$, $SD = 4.1\%$) from lying, $t(2491) = -0.66$, $p = .617$.

Across trials where the net gain to sender was above 30 ($M = 5.1\%$, $SD = 3.6\%$) and

below 30 ($M = 5.6\%$, $SD = 4.2\%$) there showed to be no significant difference either,

$t(2487) = 1.9$, $p = .241$. This was also the case for when net loss to the receiver was above

30 ($M = 5.1\%$, $SD = 3.6\%$) and below 30 ($M = 5.1\%$, $SD = 3.6\%$), $t(2487) = 1.3$,

$p = .376$.

Cluster Analysis

Hierarchical clustering was used to fit suitable clusters based on the pairwise distance measure calculated between trials using Dynamic Time Warping. Using the Pseudo F statistic and a cluster limit of 20, it was deemed that two clusters represented the best degree of separation and internal cohesiveness. The two clusters, cluster 1 and 2 were made up of 1006 and 1483 trials, respectively.
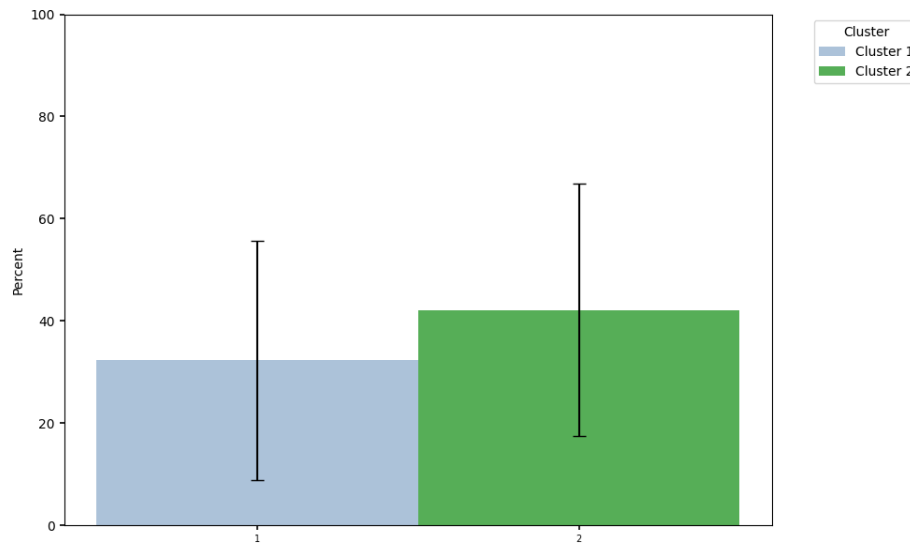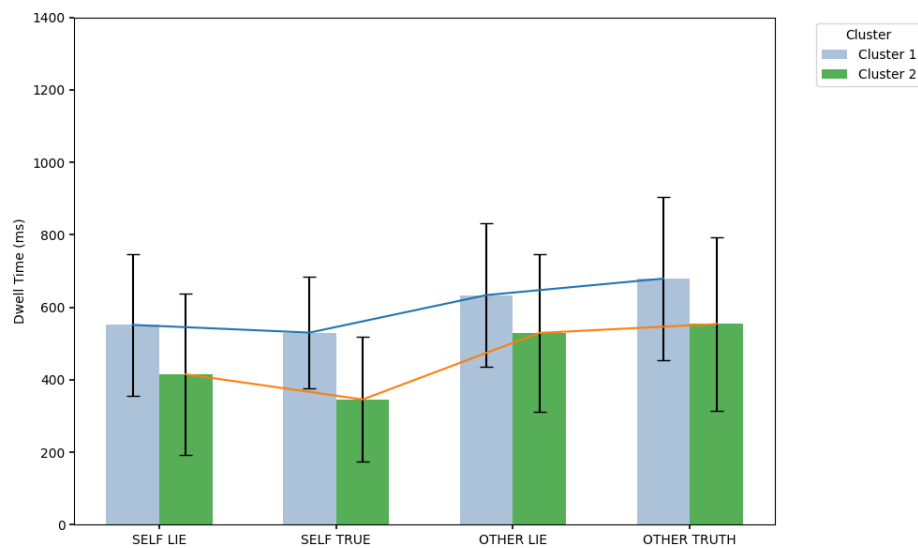
Lie Percentage

Figure 19

Average percent lies across clusters formed from hierarchical clustering based on DTW measure

There was a significant difference in the proportion of lies across clusters $\chi^2(1, N = 2489) = 24$, $p =< .001$.

Dwell Times

Figure 20

Average dwell time across clusters for each AOI.

Each of the AOIs showed significant differences across clusters, as seen in Table 5.

	Cluster 1		Cluster 2		Between		
	M (ms)	*SD* (ms)	*M* (ms)	*SD* (ms)	*t*	d.o.f.	*p*
SELF LIE	551	392	415	345	8.1	2321	<.001
SELF TRUE	530	309	345	345	14	2305	<.001
OTHER LIE	633	396	529	435	6.0	2287	<.001
OTHER TRUTH	679	452	554	479	6.6	2237	<.001

Note. d.o.f., in this case, is shorthand for degrees of freedom.

Table 5

Mean, standard deviation and t tests for the average dwell time of each AOI across participant clusters (FDR corrected).
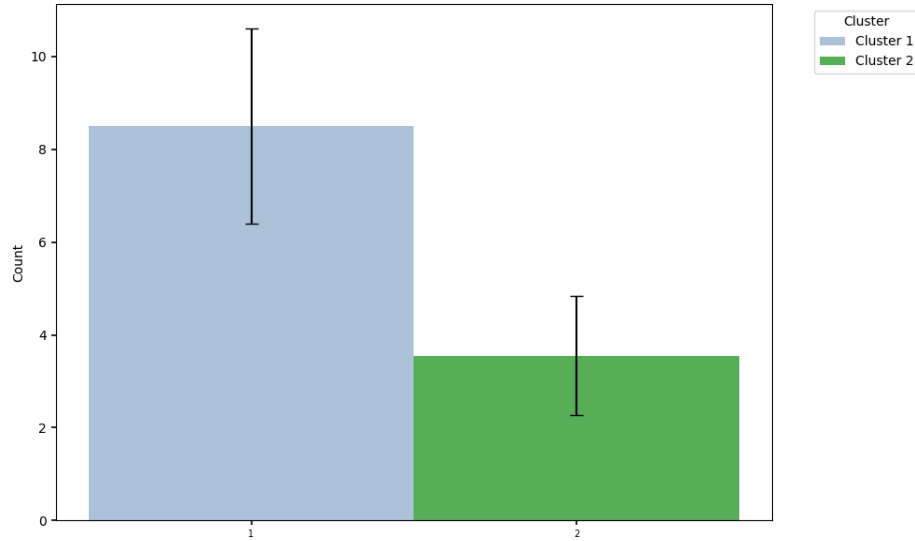
Number of Transitions

Figure 21

Average number of transitions calculated per cluster for each participant.

The average number of transitions across clusters also showed significant differences. With cluster 1 showing a mean level of 8.5 ($SD = 4.1$) and cluster 2 showing a smaller average of 3.5 ($SD = 2.6$), $\chi^2(1, N = 2027) = 24$, $p < .001$.
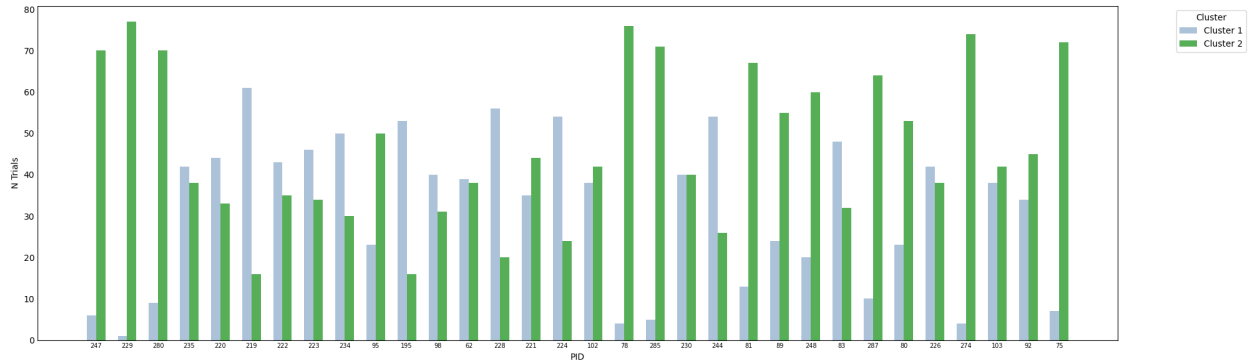

Figure 22

The number of trials per cluster for each participant. Clusters were calculated using hierarchical clustering based on DTW measure

It was observed that every participant had trials belonging to each of the cluster

memberships, as seen in Figure 22. The mean amount of trials for a given participant that

belonged to cluster 1 was 31 trials ($SD = 18$) with a 12 (Q1) - 45 (Q3) interquartile range.

Cluster 2 had a mean of 46 trials ($SD = 19$) per participant and a 32 (Q1) - 64 (Q3)

interquartile range.

Regression Analysis

A hierarchical logistic regression model was built to evaluate the usefulness of task

condition and cluster membership in predicting whether a given trial was likely to result in

the Sender choosing to lie. The model assessed gain to Sender, loss to Receiver and cluster

membership as predictors using random intercepts for participants. It also assessed

whether there was any interaction between the two task conditions and cluster.

In the resulting model, gain to sender showed to have a significant positive effect on lie

probability, $\beta = 0.14$, $SE = 0.01$, $p = < .001$ Each unit of increase in self-gain resulted in

the odds of lying increasing by approximately 15.5% ($OR = 1.15$). Loss to receiver showed

to have a significant negative effect on lie probability $\beta = -0.09$, $SE = 0.01$, $p = < .001$

with the odds of lying decreasing by approximately 8.5% for each unit of increased loss

($OR = 0.91$). Cluster showed to, also, have a significant effect on lie probability $\beta = 0.58$,

$SE = 0.20$, $p = < .001$. Cluster 2 participants were 78.2% more likely to lie than Cluster 1

participants ($OR = 1.78$)

The interaction between self gain and cluster was shown to be significant, $\beta = -0.04$,

$SE = 0.01$, $p = < .001$. This suggests that the effect of self-gain on the likelihood of lying

was weaker in Cluster 2, where each unit increase in gain to Sender was associated with a

decrease in the odds of lying by approximately 4.4% ($OR = 0.96$). In Figure 23, it can be

seen that the probability of a lie is lower for cluster 1 than it is for cluster 2, however, at

very high values cluster 1 showed the greater likelihood.

The interaction between other loss and cluster was found not to be significant, $\beta = -0.02$,
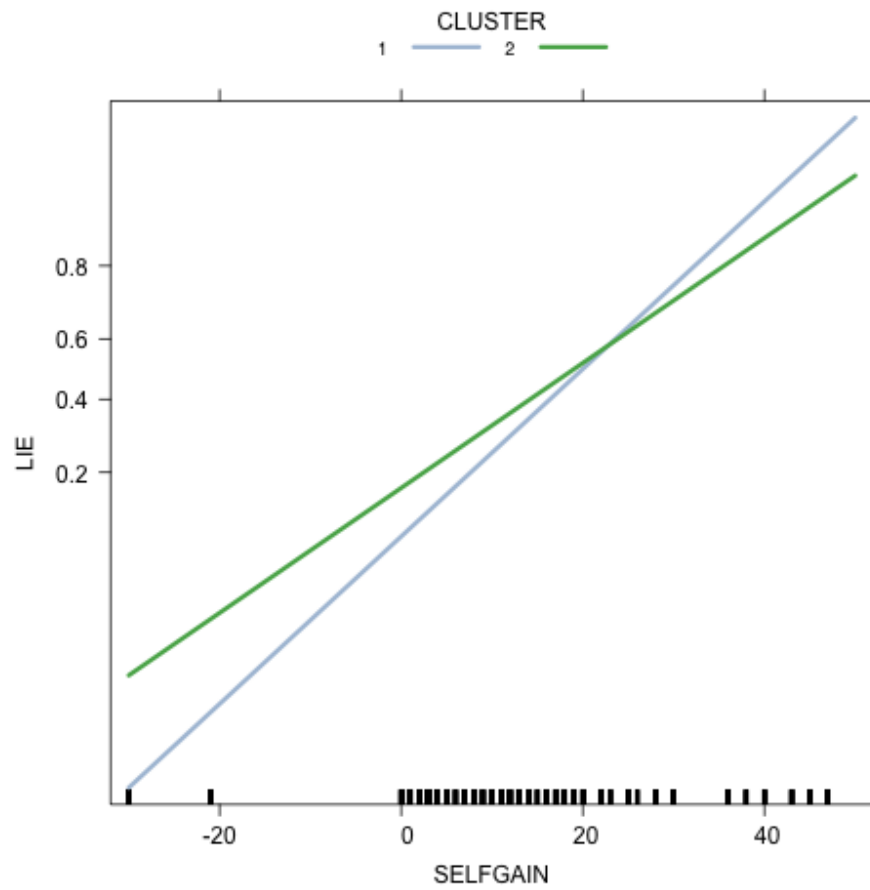
$SE = 0.01$, $p = .115$.

Figure 23

The probability that lie will be the response as self gain increases for both clusters.
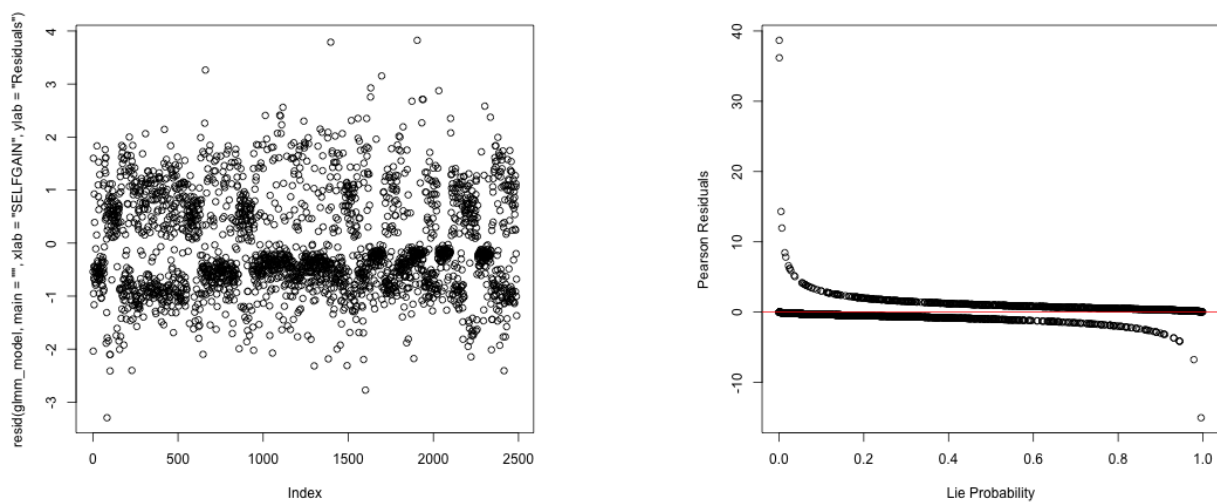
Model Diagnostics

Figure 24

(left) Residuals plot with index of observation on x-axis (right) Pearson residuals plot

The plots in Figure 24 show some noticeable outliers. The Pearson residuals plot reflects
attributes associated with heteroscedasticity around probabilities that represent almost
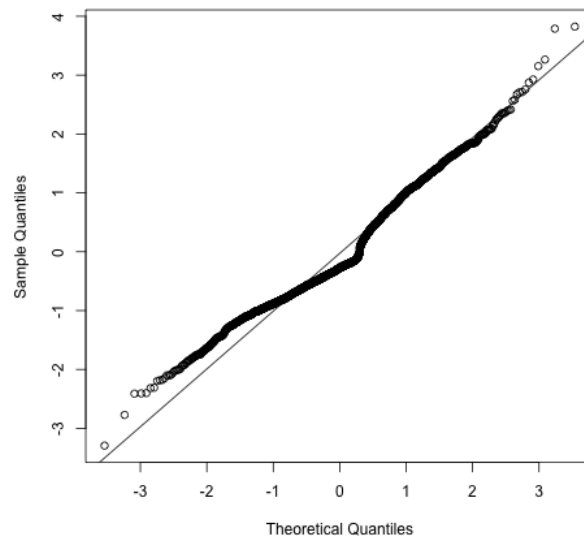certainty.

Figure 25

Q-Q plot mapping the theoretical normal distribution of quantities on to the sample ones

The Q-Q plot echoes similar aspects of the model with outliers at the upper and lower most quantiles. The model shows a better fit above the central tendency, suggesting that it is better at predicting lies than truths.

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