2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)

Investigating Gender Differences in Temporal Dynamics during an Iterated Social Dilemma: an Automatic Analysis Using Networks

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Abstract—**Emotions have a temporal nature and very often personality traits and underlying psychological conditions are hidden in the dynamics of those expressions. Within this work, we investigate the dynamics of the facial displays of dyads during an iterated social dilemma. We focus on the effect of gender and gender-pairing on those behaviors. We use networks to capture the temporal dynamics and create measures of inter- and intra- personal dependencies of emotional states. Our analysis on an iterated prisoner's dilemma corpus suggests that there are gender differences on the transitions of the emotional states and the degree of emotional influence from the opponent.**

1. Introduction

Most research focuses on the static emotions. However, emotions have a temporal nature [1] and their dynamics sometimes affect how people perceive the sender [2] or can relate to psychological conditions [3], [4]. In the case of dyadic interactions, specifically, interpersonal dynamics can reflect traits of the dyad such as cooperation [5], [6], well-being [3], or liking [7]. Moreover, inter-personal nonverbal interdependencies can often shed light on group dynamics and social roles (e.g., leader), including gender dependent social roles [8], [9], [10]. One way to explore such dynamics is in the context of social dilemmas and negotiations [5], [11], [12], [13]; people often exchange emotional signals that help resolve the situation, for example, by signaling cooperative intention or a tough stance to prevent exploitation [11].

In this work, we investigate the temporal dynamics of emotion interdependencies in an iterated social dilemma. We automatically capture meaningful measures for intra- and interpersonal influence from a previous point in time to the next one, and employ autoregressive models and network representation, inspired by relevant work [3]. We focus on gender differences. The paper is organized as follows: Section 2 covers related work. Section 3 describes the iterated prisoner's dilemma (IPD) corpus. In Section 4, we describe the networks used for our analysis. In Section 5, we discuss the results of the gender analysis. Finally, we close with discussion in Section 6 and conclusion.

2. Related work

Most research focuses on the occurrence or intensity of emotional states and expressions, however there is important information in the dynamics. Studies have investigated aspects of the dynamics, such as smile duration and apex properties, finding that people not only perceive those differences, but also assign different social meaning [2]. Moreover, differences in the dynamics of a smile can be an indicator of psychological distress such as depression [4].

Bringmann et al. propose the use of networks to study multivariate psychological processes [3]. Through this approach, psychological constructs, such as emotional states, are represented as complex systems of interacting components. A network perspective leads to insightful visualizations of the state dynamics and offers new tools to study dynamical processes. In related studies, networks were used to model temporal dynamics of emotional states, obtained by subject self reports on a daily basis, and properties of the dynamics have been linked to psychological conditions such as depression or traits such as neuroticism [3], [14]. Networks have also been used to assess intra-personal emotional interdependence of couples as a sign of well being in relationships [15]. In all of these studies emotional states were self reported by the subjects.

The dynamics in a dyadic interaction have often been looked at [6], [7], [16], but usually in terms of emotional synchrony or mimicry. Specifically, mimicry has been found to happen in affiliative circumstances and usually in in-group settings, rather than in antagonistic frames of mind [6], [7]. In competitive tasks, neutral reciprocation has also been shown to associate with cooperation [5].

In terms of gender, one may expect differences in the way male and female participants process emotion, both as an internal process (self-regulation) and as an external signal (partner-influence). This is based on a long line of research showing that men and women sometimes behave differently, often lead by societal norms on gender roles [8], [9], [17], [18]. An interesting observation comes from gender role theory, which maintains that societal gender roles influence group behavior. According to this theory, sex differences in emergent leadership in groups are due primarily to role-induced tendencies for men to specialize more than women in behaviors strictly oriented to their group's task and for women to specialize more than men in socially facilitative behaviors [10]. In general, in occidental cultures, females tend to be more communal, collaborative, and expressive than males (affiliative traits), whereas males tend to be more agentic, competitive and instrumental (assertive traits) [18].

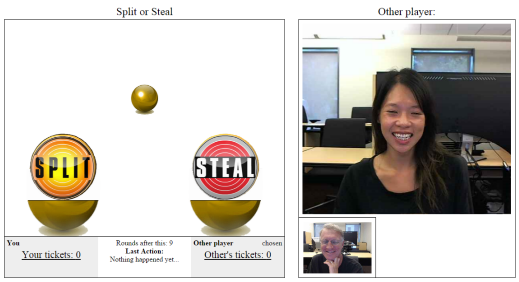

Figure 1. IPD corpus collection interface. The IPD task was framed after the TV game show, *Golden Balls* as a *Split/Steal* game. Participants see each other via webcam on a Skype-like interface.

TABLE 1. POPULATION BREAKDOWN FOR IPD CORPUS

Player	Opponent Male (_M)	Female (_F)	Total
Male (*M_*)	43	42	85
Female (*F_*)	52	49	101
Total	95	91	186 dyads

However, it has been discussed that the extend to which any of those gender differences emerge depends on gender salience, the prototype of which can change based on circumstances. For example, gender salience can be amplified in cases of mixed sex interactions, where the perceived gender distinction is greater [18]. Thus, the intergroup nature of social context and the extent to which gender defines the task can influence the degree to which communication is gender-based.

Within this work, we employ a network approach on high resolution temporal signals extracted automatically from videos of dyads during an iterated social dilemma task. There is limited work on automatic analysis of expressions in social dilemmas (perhaps with the exception of a recent study looking at sentiment [19] on a broad level), and as far as we know this is one of the first analyses of temporal phenomena in this setting. We specifically focus on gender differences.

3. Iterated Prisoner's Dilemma Corpus

3.1. Data

For this study we received and analyzed the Iterated Prisoner's Dilemma (IPD) corpus, described in related work [19]. This corpus consists of videos of a large number of participants (186 dyads) playing a 10 round iterated prisoner's dilemma. It also includes synchronized game event and statistics (player decisions and score). The game interface can be seen in Figure 1.

The IPD interaction between participants is nonverbal only (there was no audio feed in the video) so facial expression exchanges are decoupled from speech motion patterns. However, this data is sparse in expression occurrence, making the task of emotion analysis challenging. The nature of this particular data is interesting for temporal analysis. Partners can do well if they both collaborate but the structure of the task creates an incentive to exploit one's partner for greater benefits and thus, people may choose non-cooperation not only out of greed, but also through

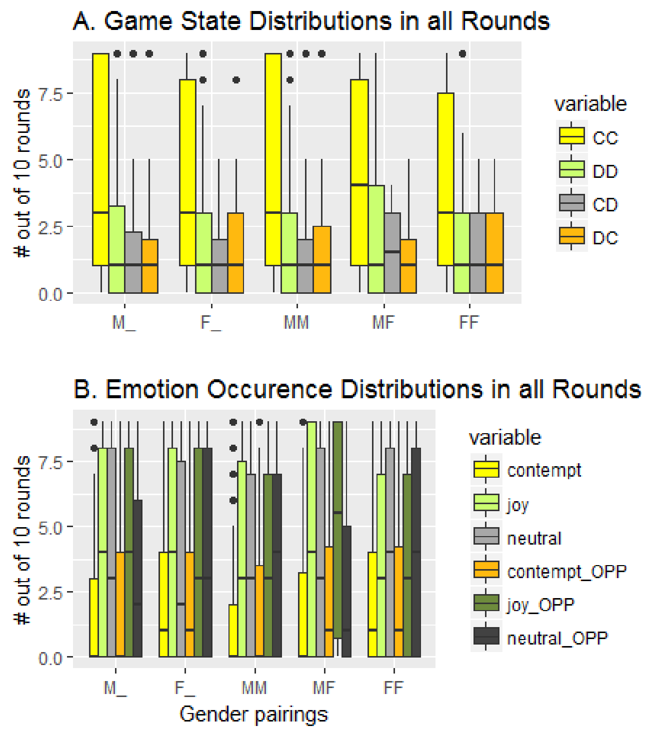

Figure 2. Distributions of game state outcome and expression occurrence for player (e.g., contempt) and player opponent (e.g., contempt_OPP) by gender (e.g. M_: male) and gender pairing (e.g., MF: male player with female opponent). No effect of gender observed for game decision outcome (A). However there are some gender effects in expression occurence (B). Mainly, females showcase more instances of joy and less of neutral when paired with male opponents.

fear of being exploited. Researchers have argued that emotional expressions allow people to solve this dilemma by communicating important information about the partner's emotions and intentions [20]. Participant dataset breakdown for gender can be seen in Table 1.[1]

3.2. Behaviors in IPD

In terms of game outcome, in IPD there are 4 possible states depending on player decisions: mutual Cooperation *(CC)*, player being defected upon *(CD)*, player defecting on opponent *(DC)* and mutual defecting *(DD)*. We show the distributions of those states by gender and gender- pairing in Figure 2A. Overall, there are significantly more CC states than any other state in the game. There are no significant gender differences observed on the game behavior distributions.

In terms of expressed behaviors, we extract automatic emotion labels from the videos of the data using a commercial software based on CERT [21]. Videos are analyzed per frame for 10 emotion labels: *anger, contempt, disgust,*

1. Analysis is based on the reported sex of the participant, partly annotated by the experimenters and partly obtained via self report from a questionnaire, however the behaviors that we study relate to social norms and thus we use the social construct of gender to refer to the groups. Since self reports are not available for all the participants, to better reveal which gender they identify with, we accept the possibility that there may be some cases where the sex does not align with the gender we assigned for analysis

joy, fear, sadness, surprise, neutral, confusion, frustration. For analysis we keep only the emotion states that have high occurrence (are activated in above 20% of the frames) in our data, namely: *contempt, joy, neutral*. Distributions of the occurrence of those expressions by gender and pairing are shown in Figure 2B. Notably, there is significantly more occurrence of joy shown by female participants when they play in an inter-gender pairing (t=2.52, p<.05 in FMvsFF), than in a same-gender pairing. Also, females show significantly less neutral (are more expressive) when playing against male participants (t=-1.72, p<.1 in FMvsF_,and t=-2.39, p<.05 in FMvsFF).

4. Network Analysis

In this section we describe how we constructed the networks for this task and the measures we extracted for analysis.

4.1. Constructing the Graph Networks

Similar to Bringmann et al. [3], we are using a multivariate autoregressive (VAR) model where each state is regressed on its own lagged values (autoregressive effect) in time $t-1$, and the lagged values of all other states from self (player) and the opponent (cross-lagged effects). To assess individual data from the population network, we create the model as a multilevel mixed effects VAR model, which collects random person-specific effects.

Game Decision Networks: The regressions for the behavior models look as follows, where t is the time of the observation (given the round-based structure of the task we chose $t = R_i,\ i = \{2, ..., 10\}$ a round of the IPD , so $t-1 = R_{i-1}$ would be the previous round):

$$state_t \sim CC_{t-1} + CD_{t-1} + DC_{t-1} + DD_{t-1} + (...)|s\_id, \quad where\ state = \{CC, CD, DC, DD\} \tag{1}$$

$$decision_t \sim pickC_{t-1} + oppPickC_{t-1} + (...)|s\_id, \quad where\ decision = \{pickC, oppPickC\} \tag{2}$$

The notation $(...)|s\_id$ is used for abbreviation and means we collect random effects for the variables in the equation per participant (with subject id s_id). A visualization of the game state network for all population can be seen in Figure 3[2]. In both the state and the decision relationships with their lagged values, there are no significant gender effects.

Emotion state networks: Following the same notation, the regressions for the emotion state network are as follows:

$$\begin{aligned} emotion_t \sim\ & contempt_{t-1} + joy_{t-1} + neutral_{t-1} + \\ & + contemptOPP_{t-1} + joyOPP_{t-1} + baselineOPP_{t-1} + \\ & + (...)|s\_id, \\ & where\ emotion = \{contempt, joy, neutral, \\ & contemptOPP, joyOPP, neutralOPP\} \end{aligned} \tag{3}$$

Based on those, and for $t = Ri$ we create the network for average population in Figure 4. Given the nature of emotion dynamics though we also create this network for $dt = 1s$, and investigate the different effects that emerge (Figure 5).

2. For visualization of the networks we use *qgraph* package in R [22]

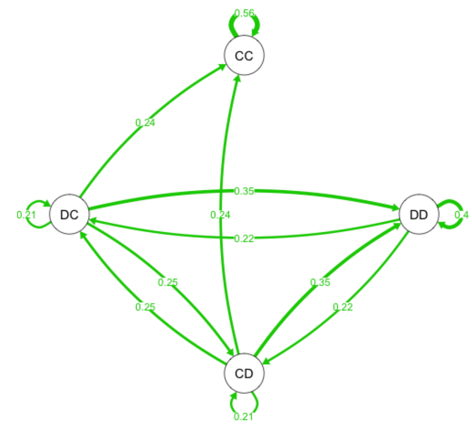

Figure 3. Game state dynamics on a round level modeled by Equations 1. Most people stay on a CC or DD loop.

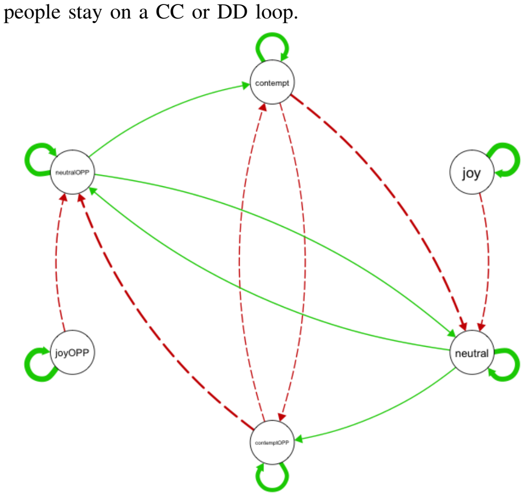

Figure 4. Average population emotion dynamics on a round level in human to human interaction during an iterated social dilemma task. Graph includes nodes for player and opponent as well. Green solid lines represent positive effect, whereas red dashed lines represent negative effect. In both cases line width shows intensity of the effect.

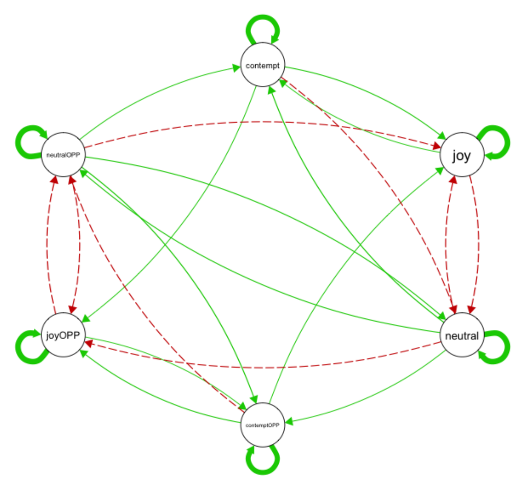

Figure 5. Average population emotion dynamics in IPD on a 1s time resolution. In this case density of significant interactions between player own states and opponent states increases.

TABLE 2. MEASURES OF INTER- AND INTRAPERSONAL EMOTIONAL INTERDEPENDENCY CREATED BY NETWORKS

	Measure	Description
	Betweenness	Centrality measure for certain node [22]
Density	*OwnInFlow, OtherInFlow*	Density of incoming connections for Player (*Own*) and Opponent (*Other*)
	OwnOutFlow, OtherOutFlow	Density of outgoing connections for Player and Opponent
	OutDegree, InDegree	Degree of in- and out-going connections for certain node [22]
Inter-personal	*OwnInFlowFromOther, OtherInFlowFromSelf*	Cross-partner density of incoming connections
	MirrorEffect	Density of same emotion incoming connections from opponent
	MirrorEffect_Node	Density of same emotion influence from opponent for certain node (e.g., influence from Joy_opp to Joy)
	MirrorEffectDeg	Degree of same emotion incoming connections from opponent
	MirrorEffect_Opp	
	FlowInNodeFromOther	Total density of incoming connections from opponent to certain node
	OtherFlowInNodeFromSelf	Total density of outgoing connections from player to certain opponent node
Intra-	*SelfLoopNode*	Node auto-regression effect from previous time
	SelfFlowInNode	Self states interdependency for certain node excluding its self loop

4.2. Extracting Measures from Networks

From the random effects collected per participant we can create networks for individual participants. We investigate traditional graph measures that have been found useful in temporal analysis of emotional states and other psychometrics [3], [22] as well as construct some measures focusing on interdependence between the participants, both overall and for specific emotional states (nodes).

We created the following measures seen in Table 2. Certain measures such as centrality were computed based on the*qgraph* R package [22]. Others, such as *MirrorEffect, OwnInFlowFromOther*, etc. were constructed to measure partner interdependence, sender and receiver effects similar to [15].

5. Emotional Interdependence and Gender

Table 3 shows the distribution differences (T test values) for all measures and for different gender pairings. Notation M_vsF_ means we compare male to female distributions, agnostic to the opponent. Similarly, MFvsFM: we compare male -paired with female opponent- to female -paired with male opponents; FMvs__: compare female -paired with male- to all participants. Only significant differences are shown in the table, for simplicity.

Overall, there are not a lot of differences between male and female player dynamics, when we are agnostic of their opponent's gender. Few exceptions suggest that there is more flow into the contempt state of an opponent when playing against a male player (ref. *OtherFlowInCONFromSelf*). However, looking at gender pairings we observe that inter-gender pairings have the most differences in the distribution and may even be driving some of the differences in the gender columns. In terms of influence, it seems that females mirror males more and receive more reinforcement into their contempt state from a male opponent, also they regulate their own emotion transitions differently when paired with a male opponent. Specifically, we see that females paired with male opponents (FM) show more mirroring overall (mostly neutral and joy) than all players (ref. *MirrorEffect, MirrorEffect_NEU, MirrorEffect_JOY* in FMvs__), and those differences are more pronounced when comparing with females in same-sex pairing (FMvsFF). Moreover, females in inter-gender pairs show more flow towards the joy state and less flow towards the neutral state in their transitions (ref. *MyFlowInNEU,MyFlowInJOY* in FMvsFF). Comparing intrapersonal with interpersonal influence it seems that the main effect is on the intra-personal regulation of emotions (*MyFlowInJOY* rather than *FlowInJoyFromOther*).

Increasing the time resolution of the analysis we reveal more effects in terms of instantaneous emotion interdependencies. Measures related to player influence for 1s intervals are shown in Table 4. We are looking if the effect on dynamics on round level is representative of the dynamics in a microlevel (1s). Further, we aim to decouple sender and receiver in the emotional exchanges which may not be apparent in a round level analysis. In this case, gender differences are revealed even in opponent agnostic cases. Specifically, we see that male players contribute less in the density of the network than female players (*Ownoutflow*) and influence less the emotions of their opponents than female players (*OtherInFlowFromSelf*). When playing against a male opponent a player also shows significantly more mirroring of joy than when playing against females. Looking at the last column (MFvsFM) of Table 4 one may also notice that differences are pronounced in inter-gender pairings again. The strongest effect suggests that females mirror the joy of male opponents significantly more than male do of female opponents (ref. *MirrorEffect_JOY_Opp* in MFvsFM).

6. Discussion

We expected effects in the game behaviors, however, no significant ones were directly obvious from this analysis. Perhaps this task can be considered gender-neutral in its definition, thus promoting participants to see themselves more as individuals focusing on their goals rather as members of a gender group. In this case, gender roles would have diminished effect on the game behaviors [18].

When looking at the expressed emotions however, we uncovered that gender differences are potentiating in mixed-sex pairings, which agrees with literature on the role of gender salience.

Interestingly, different effects revealed themselves at a 1s level of analysis, perhaps hinting that on a microlevel there are different dynamics, whereas on a round level people may be regulating behavior to fit certain roles.

We wanted to mention a limitation of this method, which is a restrain on the degrees of freedom for the states of the VAR model. By including the opponent we double the states and to collect random effects per participant we need to keep

TABLE 3. Inter-and Intra- personal emotional interdependency by gender and pairing- Modeled on the Round level. T values reported with significance levels: ***, $p < .001$, **,$p < .01$, * $p < .05$, . $p < .1$

		Measure	M_vsF_	_Mvs_F	MMvs__	MFvs__	FMvs__	FFvs__	MMvsMF	FMvsFF	MFvsFM
Centr	Player	BetweennessCON		1.692.							-1.677.
	Opp	BetweennessCONopp					-1.928.				
Density Measures	Player	OwnInFlow					1.784.				
		InDegreeCON									
		InDegreeJOY					1.715.				
		InDegreeNEU				1.663.	2.047*			2.015*	
	Opp	OtherInFlow				1.922.			-1.826.		
		InDegreeCONopp									
		InDegreeJOYopp	2*			1.907.					1.903.
		InDegreeNEUopp				2.082*			-1.817.	1.678.	
	Player	OwnOutFlow				2.22*			-2.061*		
		OutDegreeCON					1.749.			1.902.	
		OutDegreeJOY									
		OutDegreeNEU				1.853.					
	Opp	OtherOutFlow				1.798.	1.843.			1.691.	
		OutDegreeCONopp				2.038*			-1.693.		
		OutDegreeJOYopp									
		OutDegreeNEUopp					1.756.			1.801.	
Interpersonal Measures	Player	OwnInFlowFromOther					1.841.				
		OtherInFlowFromSelf				1.979.					
		MirrorEffect					2.38*			2.658**	
		MirrorEffect_CON									
		MirrorEffect_NEU					1.974.			2.287*	
		MirrorEffect_JOY					2.04*			2.469*	
		MirrorEffectDeg	-1.871.		-2.184*		1.813.			1.873.	-1.807.
	Opp	MirrorEffect_Opp				2.445*			-2.351*		
		MirrorEffect_CON_Opp									
		MirrorEffect_NEU_Opp				2.045*			-1.988*	1.791.	
		MirrorEffect_JOY_Opp									
		MirrorEffectDegOpp			-1.842.				-2.302*		
	Player	FlowInCONFromOther		2.046*			1.71.			2.376*	
		FlowInNEUFromOther									
		FlowInJOYFromOther								1.671.	
	Opp	OtherFlowInCONFromSelf	1.93.								
		OtherFlowInNEUFromSelf									
		OtherFlowInJOYFromSelf									
Intrapersonal Measures	Player	MyFlowInCON		2.114*				-1.674.		2.077*	
		SelfLoopCON					-1.762.			-1.992*	
		MyFlowInNEU					-2.078*			-2.144*	
		SelfLoopNEU									
		MyFlowInJOY		1.684.			2.612*			3.039**	
		SelfLoopJOY									
	Opp	OtherFlowInCON	1.791.								
		SelfLoopCON_Opp				-1.683.					
		OtherFlowInNEU				-2.183*			1.929.		
		SelfLoopNEU_Opp									
		OtherFlowInJOY				2.593*			-2.105*		
		SelfLoopJOY_Opp									

the complexity of the model low. On a round level analysis, this discouraged from using facial action units (AUs) as units of analysis, where we would need a greater number of states.

Finally, we would expect context based analysis including events to give more insights, especially in round based models where affect is influenced potentially by the result of the round.

7. Conclusion

We presented an automatic capture of temporal dynamic properties of emotions and game decisions for participants interacting in an iterated social dilemma, using networks. We uncovered gender differences, especially pronounced in inter-gender pairings, and dynamics that change when looking at different timeframe of analysis. As future work, using the network analysis it would be interesting to investigate closer the emerging leadership in an interaction, both in game behaviors and emotional exchanges.

Acknowledgments

This work was supported by the U.S. Army Research Laboratory under contract W911NF-14-D-0005. Any opinion, content or information presented does not necessarily reflect the position or the policy of any Government, and no official endorsement should be inferred.

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TABLE 4. INTER-AND INTRA- PERSONAL EMOTIONAL INTERDEPENDENCY BY GENDER AND PAIRING- MODELED ON 1SEC LEVEL. T VALUES REPORTED WITH SIGNIFICANCE LEVELS: ***, $p < .001$, **,$p < .01$, * $p < .05$, . $p < .1$

	Measure	M_vsF_	_Mvs_F	MMvs__	MFvs__	FMvs__	FFvs__	MMvsMF	FMvsFF	MFvsFM
Interpersonal Measures	OwnInFlowFromOther		-2.364*		1.875.			-1.925.		
	OtherInFlowFromSelf	-3.135**				1.96.	1.894.			-1.789.
	MirrorEffect									
	MirrorEffect_CON									
	MirrorEffect_NEU		-1.773.		1.7.			-1.987*		1.758.
	MirrorEffect_JOY		3.099**		-2.259*	2.417*		2.454*	1.924.	-3.63***
	MirrorEffect_Opp		-1.748.				1.827.			
	MirrorEffect_CON_Opp									
	MirrorEffect_NEU_Opp	-2.089*		-1.806.						
	MirrorEffect_JOY_Opp	2.746**			2.125*	-1.884.				3.103**
	FlowInCONFromOther	-1.697.								
	FlowInNEUFromOther		-1.749.					-2.006*		
	FlowInJOYFromOther		3.587***		-1.942.	2.709**		2.351*	2.711**	-3.515***
	OtherFlowInCONFromSelf			-1.764.				-2.223*		
	OtherFlowInNEUFromSelf	-2.165*		-1.783.						
	OtherFlowInJOYFromSelf	3.338***			2.698**	-2.218*				3.745***
Intrapersonal Measures	MyFlowInCON									
	SelfLoopCON					-2.25*				
	MyFlowInNEU	1.702.				-2.205*				1.72.
	SelfLoopNEU									
	MyFlowInJOY	-2.272*		-2.06*				-1.656.		
	SelfLoopJOY									
	OtherFlowInCON							-1.845.		
	SelfLoopCON_Opp				-2.065*			1.813.		
	OtherFlowInNEU		1.973*		-2.089*			2.792**		
	SelfLoopNEU_Opp									
	OtherFlowInJOY		-2.098*	-2.031*				-2.249*		
	SelfLoopJOY_Opp							1.711.		

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