Methodologies for electroencephalographic profiling of achievement, affiliation and power motivation using a computer game

Author:
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Publication Date:
2018

DOI:
https://doi.org/10.26190/unsworks/21242

Methodologies for Electroencephalographic Profiling of Achievement, Affiliation and Power Motivation Using a Computer Game

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A thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy at the
School of Engineering & Information Technology
University of New South Wales

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Abbreviation for degree as give in the University calendar	:	**PhD**
Faculty	:	**UNSW Canberra**
School	:	**School of Engineering and Information Technology**
Thesis Title	:	**Methodologies for Electroencephalographic profiling of achievement, affiliation and power motivation using a computer game**

Abstract 350 words maximum: (PLEASE TYPE)

Understanding and modelling player experience helps us to design games that satisfy various player's needs. Current player models focus on behaviour, cognition and emotion, but player motive profiles have not been fully studied. The focus of this thesis is on three types of motivation profiles: achievement, affiliation and power. Existing motivation measurements include subjective methods and objective methods. However, it is the lack of an automatic, objective measurement method that motivates the work in this thesis. Electroencephalography measures brain signals during gameplay without interrupting players. Therefore, electroencephalographic signals can be regarded as a promising way to measure player motivation profiles.

In this thesis, we aim to develop methodologies to assess achievement, affiliation and power motivation of computer game players using electroencephalographic signals during game play. First, we designed a mini-game for identifying achievement, affiliation and power motivation in a strategic decision-making scenario. Then a human experiment was conducted to collect three kinds of data: player behaviour, electroencephalographic signals and psychological test data. Based on three subject labelling schemes using the psychological test output, we examined the effectiveness of using player behaviour and electroencephalographic signals to classify player motivation in the proposed mini-game.

Results showed that electroencephalography-based measurement revealed motivation better than the behaviour-based measurement. According to the proposed mini-game, money and satisfaction features of non-player characters related to risk-taking and social behaviour respectively. The behaviour of non-player characters such as *random* and *tit for tat* strategies were good choices for evoking human social attitude. *Always defect*, *random* and *tit for tat* were good choices for evoking human risk-taking attitudes. However, *always cooperate* was the least useful strategy for reflecting social and risk-taking attitudes. Also, the findings identified the most significant electroencephalographic features for assessing achievement, affiliation and power motivation in the proposed mini-game.

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Abstract

Understanding and modelling player experience helps us to design games that satisfy various players' needs. Current player type models focus on behaviour, cognition and emotion, but player motive profiles have not been fully studied. The focus of this thesis is on three types of motivation profiles: achievement, affiliation and power. These were chosen because they form the basis for identifying other motivation profiles such as Bartle's achievers, socialisers, killers and explorers. Existing motivation measurements include subjective methods such as questionnaires, the thematic apperception test, and the multi-motive grid method, as well as objective methods such as behavioural analysis. However, it is the lack of an automatic, objective measurement method that motivates the work in this thesis. Electroencephalography measures brain signals during gameplay without interrupting players. One of its advantages is that signals are acquired from involuntary processes, which reduces the chance of external manipulation of these signals. Therefore, electroencephalographic signals can be regarded as a promising way to measure player motivation profiles.

In this thesis, we aim to develop methodologies to assess achievement, affiliation and power motivation of computer game players, using electroencephalographic signals collected during game play. First, we designed a mini-game for identifying achievement, affiliation and power motivation in a strategic decision-making scenario. Then a human experiment was conducted to collect three kinds of data: player behaviour, electroencephalographic signals and psychological test data. Based on three subject labelling schemes using psychological test output, we examined the

possibilities of using player behaviour and electroencephalographic signals to classify player motivation in the proposed mini-game. We then examined the effectiveness of using the proposed mini-game to profile player motivation. Non-player characters in the proposed mini-game have their own monetary winnings, satisfaction level, and different strategies to play the game. We used player behaviour and electroencephalographic signals collected during a game to validate the design of game mechanics, non-player characters and plot of the game scenario. Finally, a conceptual model that links psychological motivation theory to electroencephalography was proposed and validated. Correlation analysis between electroencephalographic features and motivation variables, and an in-depth analysis of electroencephalographic features were used to assess player motivation, while critical frequency bands and brain regions of achievement, affiliation and power motivation were identified.

Our results showed that electroencephalography-based measurement revealed motivation better than the behaviour-based measurement. Therefore, electroencephalography is a promising way to measure player motivation when players play a game. According to the proposed mini-game, money and satisfaction features of non-player characters related to risk-taking and social behaviour respectively. In addition, the behaviour of non-player characters such as *random* and *tit for tat* strategies were good choices for evoking human social attitude. *Always defect*, *random* and *tit for tat* were good choices for evoking human risk-taking attitudes. However, *always cooperate* was the least useful strategy for reflecting social and risk-taking attitudes. In terms of the the most useful electroencephalographic features for assessing motivation, frontal alpha, temporal gamma and several event-related potentials in the anterior cingulate cortex were identified.

This work provides theoretical and numerical foundations for future research into human-machine interactions, simulation training and a variety of artificial intelligence fields.

Acknowledgement

My four years of PhD study at UNSW Canberra hold previous memories for me. When I first started this journey, I never realized it would be such a life-transforming and memorable experience for me. I would like to thank my supervisors, my family, friends and colleagues who have helped me with this study. My research would have been impossible without their support.

I am deeply grateful to my supervisors A.Prof Kathryn Kasmarik and Prof. Hussein Abbass. I would like to express my sincere thanks to Kathryn for her invaluable assistance, training and advice during my study. I am so grateful for the time and energy she has spent training and educating me. I also offer my appreciation to my co-supervisor Prof. Hussein Abbass, who gave me great advice for my research and life. His support and assistance helped me through the hard days.

I am thankful to all members in Trust Autonomy Group: Dr. George Leu, Dr. Jiangjun Tang, Duy Tung Nguyen, Hung Nguyen and Min Wang for their company along this journey. I am also thankful to all my friends, Li Wang, Qian Song, Meng Xu, Rongkang Gao, Xiwen Zhai, Yi Zhu for their support and I will cherish the memories of our time together over the past four years.

My sincere thanks to my beloved parents. Their priceless love, encouragement and strength supported me throughout the candidature. I am profoundly grateful to have had my family on my side no matter what happens.

Heartfelt thanks to all the people who have helped me, to all the bitterness and sweetness I have experienced. I will become a mature person, giving my love to the people I love.

This thesis was edited by Kathie Brown of A+Academic Editing, Canberra.

Contents

Abstract **i**

Keywords **iii**

Acknowledgements **iv**

List of Publications **vi**

Table of Contents **vi**

List of Figures **xiv**

List of Tables **xxiv**

Acronyms **xxviii**

1 Introduction **1**

1.1 Motivation 1

1.2 Thesis Summary 3

1.3 Research Challenges and Questions 8

1.4 Contributions and Significance 10

1.5 Thesis Overview 12

2 Literature Review **17**

2.1 Introduction 17

2.2 Computer Games and Player Types 18

2.3 Motivation Theory 20

2.3.1 Achievement Motivation 21

2.3.2 Affiliation Motivation 22

2.3.3 Power Motivation 23

2.3.4 Measuring Motivation 24

2.4 Electroencephalography as an Approach to Measuring Motivation . . 30

2.4.1 Emotion Recognition 32

2.4.2 Risk-taking 37

2.4.3 Social Factors 42

2.5 Conclusion 44

3 An Abstract Mini-Game for Assessing Motivation **45**

3.1 Introduction 45

3.2 Conceptual Models Linking Player Motivation and Electroencephalography 46

3.2.1 Flow Models 46

3.2.2 Risk-taking and Social Attitudes 48

3.3 Game Design 50

3.3.1 Storyline 50

3.3.2 Game Mechanics 52

3.3.3 Non-player Characters 53

3.3.4 Gameplay 58

3.4 Discussion 60
3.5 Conclusion 61

4 Experimental Protocol and Participant Demographics 63

4.1 Introduction 63
4.2 Experimental Protocol 64
4.2.1 Welcome 64
4.2.2 Electroencephalography Setup 65
4.2.3 Introduction and Tutorial Phase 66
4.2.4 Individual Play Phase 67
4.2.5 Self-Reported Emotion 69
4.2.6 Social Network Phase 70
4.2.7 Multi-motive Grid Test 71
4.3 Subject Demographics and Statistical Data 72
4.3.1 Age and Gender 72
4.3.2 Multi-Motive Grid Statistics 72
4.3.3 Behavioural Statistics 72
4.3.4 EEG Signal Sample 74
4.4 Conclusion 77

5 Classifying Motivation From Player Behaviour and Electroencephalographic Data 79

5.1 Introduction 79
5.2 Classifying Player Motivation from Player Behaviour 80
5.2.1 Aim 80
5.2.2 Hypothesis 80

5.2.3 Method 80

5.2.4 Results and Discussion 85

5.3 Classifying Player Motivation from Electroencephalographic Data . . 88

5.3.1 Aim 88

5.3.2 Hypothesis 89

5.3.3 Method 89

5.3.4 Results and Discussion 95

5.4 General Disucssion 102

5.5 Conclusion 103

6 Analysing the Design of Our Mini-game for Player Motive Profiling 105

6.1 Introduction 105

6.2 Analysing Play Strategies of Non-player Characters for Assessing Motivation 106

6.2.1 Aim 107

6.2.2 Hypothesis 107

6.2.3 Method 107

6.2.4 Results 112

6.2.5 Discussion 115

6.3 Analysing Features of Non-player Characters for Assessing Motivation 116

6.3.1 Aim 117

6.3.2 Hypothesis 117

6.3.3 Method 118

6.3.4 Results 120

6.3.5 Discussion 128

6.4 Analysing Individual Play and Social Network Phases for Assessing Motivation 129
6.4.1 Aim 129
6.4.2 Hypothesis 129
6.4.3 Method 130
6.4.4 Results 130
6.4.5 Discussion 134
6.5 Conclusion 135

7 Identifying Electroencephalographic Features for Player Motive Profiling 137
7.1 Introduction 137
7.2 Identifying EEG Features for Assessing Player Motivation from Literature 138
7.2.1 Aim 139
7.2.2 Hypothesis 139
7.2.3 Method 142
7.2.4 Results 142
7.2.5 Discussion 147
7.3 Identifying EEG Features for Assessing Player Motivation using Machine Learning 148
7.3.1 Aim 148
7.3.2 Hypothesis 148
7.3.3 Method 149
7.3.4 Results 153
7.3.5 Discussion 157

7.4 Conclusion 158

8 Conclusions and Discussion **161**

8.1 Introduction 161

8.2 Research Contributions and Findings 162

8.3 Limitations and Future Work 166

8.4 Concluding Remarks 168

A Friends or Fortune? A Social Network Game Booklet **169**

A.1 Introduction 169

B An Experiment that Compares Classification Techniques **187**

B.1 Aim 187

B.2 Method 187

B.3 Results 189

B.4 Summary 191

C An Experiment that Compares Artifact Removal Techniques **193**

C.1 Aim 193

C.2 Method 193

C.3 Results 195

C.4 Summary 195

D Numerical Results Supporting NPC Design **197**

D.1 Introduction 197

E An Experiment that Compares Feature Selection Methods **255**

E.1 Aim 255

E.2 Method 255
E.3 Results 256
E.3.1 Individual Play Phase 256
E.3.2 Social Network Phase 260
E.4 Conclusion 260

List of Figures

1.1 We categorise existing player types and player motivation studies into four groups, and identify areas of overlap between the groups. 5

1.2 Overview of the connecting framework for the thesis. 7

2.1 Graphical representation of the 'flow zone' 19

2.2 Subjective and objective measurements of motivations 24

2.3 An example picture and statements from a commercially available MMG test. 28

2.4 An example intepretation of MMG results as 'average', 'above average' or 'below average'. 29

2.5 Interpretation of MMG results in four situations (applicable to each of achievement, affiliation and power). 30

2.6 Three emotional states of flow associated with the circumplex model of affect. 33

3.1 Hypothesised flow zone for an affiliation-motivated individual 47

3.2 Hypothesised flow zone for a power-motivated individual 48

3.3 Comparison of different dominant motivations on axes of risk and social attitude 50

3.4 Game mechanics for accumulating 'fortune' 53

3.5 Our proposed abstract non-player characters have dimensions for money and satisfaction. 54
3.6 Differences in money accumulated by each non-player character playing theoretical opponents with different probabilities of choosing to cooperate. 57
3.7 Differences in final satisfaction of each non-player character playing theoretical opponents with different probabilities of choosing to cooperate. 57
3.8 Tutorial and individual play phase user interface 59
3.9 Social network phase user interface 60

4.1 Procedure of the experiment 64
4.2 Experimental setup and environment 65
4.3 Form to collect demographic data 67
4.4 Example of a form to collect self-reported emotions 69
4.5 Visualisation of raw MMG data: Subjects' hope versus fear components for achievement motivation 73
4.6 Visualisation of raw MMG data: Subjects' hope versus fear components for power motivation 73
4.7 Visualisation of raw MMG data: Subjects' hope versus fear components for affiliation motivation 74
4.8 Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Candy 74
4.9 Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Dan 75
4.10 Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Ruby 75

4.11 Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Vince 75

4.12 Visualisation of raw behavioural data: The number of each type of NPC which subjects chose to add to their network in SNP 76

4.13 Visualisation of raw EEG data in a particular trial. 76

5.1 Flowchart of the EEG signal processing 90

5.2 Flowchart of the epoch segmentation and feature extraction processes 93

5.3 Motivation classification performance for average, above and below subject labelling scheme (LS1) using behaviour data and EEG data in IPP and SNP 98

5.4 Motivation classification performance for H-L, L-H and other subject labelling scheme (LS3) using behaviour data and EEG data in IPP and SNP 101

6.1 Results of using ACC mu band in money and satisfaction feedback to reveal social attitude. 121

6.2 Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude. 122

6.3 Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude. 122

6.4 Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude. 123

6.5 Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude. 123

6.6 Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude. 124

6.7 Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude. 124
6.8 Performance of EEG and NPC features for predicting social attitude. 125
6.9 Using NPCs to reveal social attitude via EEG analysis 126
6.10 Performance of EEG and NPC features for predicting risk attitude. . 127
6.11 Using NPCs to reveal risk-taking attitude via EEG analysis 127
6.12 Results of using ACC mu band in the whole SNP and during action to reveal social attitude. 131
6.13 Results of using frontal alpha asymmetry in the whole SNP and during action to reveal social attitude. 131
6.14 Results of using prefrontal alpha asymmetry in the whole SNP and during action to reveal risk-taking attitude. 132
6.15 Results of using ACC ERN in the whole SNP and during action to reveal risk-taking attitude. 132
6.16 Results of using ACC MFN in the whole SNP and during action to reveal risk-taking attitude. 133
6.17 Results of using ACC P300 in the whole SNP and during action to reveal risk-taking attitude. 133
6.18 Results of using ACC TBR in the whole SNP and during action to reveal risk-taking attitude. 134

7.1 The brain regions associated with emotion, risk-taking behaviour and social factors 140
7.2 A synthesised tree of EEG signal processing for motivation types . . . 141
7.3 Relevant brain regions and frequency bands for assessing achievement, affiliation and power motivation in the abstract mini-game 156

D.1 Results of using ACC mu band in IPP and action to reveal social attitude when playing with Cooperator Candy. 198

D.2 Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Cooperator Candy. 199

D.3 Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Cooperator Candy. 200

D.4 Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Cooperator Candy. 201

D.5 Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. . . . 202

D.6 Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. 203

D.7 Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. 204

D.8 Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. . . . 205

D.9 Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. 206

D.10 Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. . . . 207

D.11 Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. 208

D.12 Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. . . . 209

D.13 Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. 210

D.14 Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. . . . 211
D.15 Results of using ACC mu band in IPP and action to reveal social attitude when playing with Defector Dan. 212
D.16 Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Defector Dan. 213
D.17 Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Defector Dan. 214
D.18 Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Defector Dan. . . 215
D.19 Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Defector Dan. 216
D.20 Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. 217
D.21 Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Defector Dan. 218
D.22 Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. 219
D.23 Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Defector Dan. 220
D.24 Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. 221
D.25 Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Defector Dan. 222
D.26 Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. 223

D.27 Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Defector Dan. 224

D.28 Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. 225

D.29 Results of using ACC mu band in IPP and action to reveal social attitude when playing with Random Ruby. 226

D.30 Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Random Ruby. 227

D.31 Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Random Ruby. 228

D.32 Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Random Ruby. . 229

D.33 Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Random Ruby. 230

D.34 Results of using Prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. 231

D.35 Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Random Ruby. 232

D.36 Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. 233

D.37 Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Random Ruby. 234

D.38 Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. 235

D.39 Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Random Ruby. 236

D.40 Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. 237
D.41 Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Random Ruby. 238
D.42 Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. 239
D.43 Results of using ACC mu band in IPP and action to reveal social attitude when playing with Vengeful Vince. 240
D.44 Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Vengeful Vince. 241
D.45 Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Vengeful Vince. 242
D.46 Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Vengeful Vince. . 243
D.47 Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. 244
D.48 Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. 245
D.49 Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. 246
D.50 Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. 247
D.51 Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. 248
D.52 Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. 249

D.53 Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. 250
D.54 Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. 251
D.55 Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. 252
D.56 Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. 253

List of Tables

2.1 Mapping a subset of player type literature to achievement, affiliation and power motivation 20

2.2 Characteristics of emotion, social attitude and risk-taking that may be observed in individuals with a given dominant motivation 22

2.3 The 12 statements of a commercially availalbe MMG. 29

2.4 Experimental scenarios, data analysis methods, associated features and brain regions in existing EEG-based emotion recognition literature 34

2.5 Experimental scenarios, data analysis methods, associated features and brain regions in existing neuroscience literature for risk-taking and decision-making 38

2.6 Experimental scenarios, data analysis methods, associated features and brain regions in existing neuroscience literature for social interaction 42

3.1 Abstract games that invoke risk-taking and/or social attitude 51

4.1 In-game event coding system for TP and IPP 69

4.2 In-game event coding system for SNP 71

5.1 Subject labelling scheme 1 (LS1) 82

5.2 Subject labelling scheme 2 (LS2) 83

5.3 Subject labelling scheme 3 (LS3) 84

5.4 Comparison of accuracy between three subject labelling schemes on player motivation classification using player behaviour from the individual play and social network phases 87
5.5 Comparison of performance between three subject labelling schemes on player motivation classification using EEG signal from the individual play and social network phases 97

6.1 Correlation coefficients between motivation variables and player behaviour with NPCs in the individual play phase 111
6.2 Correlation coefficients between motivation variables and player behaviour with NPCs in the social network phase 111
6.3 Characteristics of regression models using player behaviour in individual play phase to predict motivation profile 113
6.4 Characteristics of regression models using player behaviour in social network phase to predict motivation profile 113
6.5 Features extracted for identifying mental indicators of motive profile . 119
6.6 Hypothesis about using the conceptual model to evaluate risk-taking and social attitudes for each motivation related to the behaviour. . . 120

7.1 Features extracted for identifying mental indicators (risk-taking, social and emotion) of motive profile 140
7.2 Correlation coefficients between motivation variables and EEG features from the individual play phase 143
7.3 Correlation coefficients between motivation variables and EEG features from the social network phase 145
7.4 Correlation coefficients between motivation variables and EEG features from the regression model 146

7.5 Summary of the most effective EEG features for motivation classification identified using correlation subset evaluation in the individual play phase . . . 152
7.6 Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the individual play phase . . . 153
7.7 Summary of the most effective EEG features for motivation classification identified using correlation subset evaluation in the social network phase . . . 154
7.8 Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the social network phase . . . 154
7.9 Summary of the most effective EEG features for motivation classification using correlation subset evaluation in the regression model . . 155
7.10 Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the regression model 156

B.1 Comparison of classification accuracies among different classifiers using player behaviour from IPP . . . 190
B.2 Comparison of classification accuracies among different classifiers using EEG signal from IPP . . . 190
B.3 Comparison of classification accuracies among different classifiers using player behaviour from SNP . . . 190
B.4 Comparison of classification accuracies among different classifiers using EEG data from SNP . . . 191

C.1 Performance of Motivation classification using three different artifact removal technique . . . 195

E.1 Summary of the most effective EEG features for achievement motivation using three feature selection methods in IPP 256

E.2 Summary of the most effective EEG features for affiliation motivation using three feature selection methods in IPP 257

E.3 Summary of the most effective EEG features for power motivation using three feature selection methods in IPP 257

E.4 Summary of the most effective EEG features for achievement motivation using three feature selection methods in SNP 258

E.5 Summary of the most effective EEG features for affiliation motivation using three feature selection methods in SNP 258

E.6 Summary of the most effective EEG features for power motivation using three feature selection methods in SNP 259

E.7 Performance of player motivation classification using three different feature selection methods in IPP 259

E.8 Performance of player motivation classification using three different feature selection methods in SNP 259

List of Common Acronyms

ACC	Anterior cingulate cortex
ADJUST	Automatic EEG artifact detection based on the joint use of spatial and temporal features
ALLC	Always cooperate
ALLD	Always defect
AM Grid	The achievement motive grid
ANOVA	Analysis of variance
BCI	Brain computer interface
CMPS	The Cezarec Marks Personal Scheme
CNS	Central nervous system
DBN	Deep belief network
DDA	Dynamic difficulty adjustment
DEAP	Dataset for emotion analysis using physiological signals
DS	Differential spectrum
EEG	Electroencephalography
ERPs	Event-related potentials
ERN	Error-related negativity
FD	Fractal dimension
FIR	Finite impulse response
FK	Fear of loss of control
FM	Fear of failure
FRN	feedback-related negativity
FZ	Fear of rejection
GELM	Graph regularized extreme learning machine
GSCCA	Group sparse canonical correlation analysis
HA	Hope of affiliation
HE	Hope for success
H-H	High hope and high fear
HK	Hope of control
H-L	High hope and low fear
HMM	Hidden markov model
HOC	Higher coder crossing
IADS	International affective digitized sounds

IAPS	International affective picture system
ICA	Independent component analysis
ICs	Independent component
IG	The investment game
IIR	Infinite impulse response
IPP	Individual play phase
KNN	K-nearest neighbours
KS	Kolmogorov-Smirnov
lDFA	Linear discriminant function analysis
L-H	Low hope and high fear
L-L	Low hope and low fear
LPP	Late positive potential
MFN	Medial frontal negativity
MMG	The multi-motive grid method
MMORPGs	Massively multiplayer online role-playing games
MRMR	Minimal-redundancy-maximal-relevance
MSE	Mean squared error
NPCs	Non-player characters
PD	Prisoner's dilemma
PSD	Power spectral density
qDFA	Quadratic discriminant function analysis
RBF	Radial basis function
RFE	Recursive feature elimination
RL	Reinforcement learning
RTM	Risk-taking Model
SDT	Self-determination theory
SEED	SJTU emotion EEG dataset
SNP	Social network phase
SPN	Stimulus-preceding negativity
SVM	Support vector machine
TAT	The thematic apperception test
TBR	Theta-to-beta ratio
TFT	Tit for Tat
TP	Tutorial phase
UG	The ultimatum game

Chapter 1

Introduction

1.1 Motivation

Computer games are one of the most important forms of entertainment in our daily life. According to the latest Global Games Market Report from market intelligence firm Newzoo, around 2.3 billion gamers worldwide are projected to spend a total of $137.9 billion on games in 2018[1]. When considering the most frequent reasons why people engage in a game, we draw upon Digital Australia's 2018 report which stated that 16% of the players play games for fun[2]. This is the top reason given by players for playing games. The concept of 'flow' in the academic field has been identified as an enabler for players to have 'fun' in a game [1]. Flow is an optimal experience by people fully engaged in a game or task. It occurs when the challenge of a game perfectly matches a player's abilities [1]. In contrast, if the challenge of the game is beyond the player's abilities, it generates anxiety. When the challenge of a game is below the player's abilities, players feel bored and quit the game very quickly.

However, it is a fact that people have different abilities, as well as personalities, behaviours, preferences, and motivations. Therefore, considerable effort has been made by both academia and industry to design games that keep players in the flow

[1] https://newzoo.com/insights/articles/global-games-market-reaches-137-9-billion-in-2018-mobile-games-take-half/. Accessed: 30 April 2018

[2] https://igea.net/2017/07/digital-australia-2018-da18/. Accessed: 24 July, 2017

zone for as long as possible. Dynamic difficulty adjustment (DDA) is a method that automatically adjusts game difficulty to maintain a player in their flow zone [2]. DDA has been applied on commercial games such as *Half-Life 2* and *Max Payne*. To generate enjoyable and immersive game environments, game designers first need to understand individual differences and personal needs of players. A range of research has been developed to understand player experience in computer games. This includes understanding why different players have diverse game-play behaviours [3], why they are excited by different kinds of fun [4], how their personalities differ [5], and how their motivations differ [6–8].

Training and learning using simulation environments also benefits from flow theory [9]. Combining the study of individual differences in motivation and the design of simulation environments promotes training effectiveness by maintaining a learner's high motivation. In addition, novel applications for human motivation study in domains such as human-machine interaction and human-machine teaming continue to emerge. Human decision-making behaviour in human-machine interaction and human-machine teaming are evolving from 'in-the-loop' to 'on-the-loop' and 'out-of-the-loop' [10, 11]. Insights into the motivation states of humans provide useful information for understanding human performance in these systems.

Several psychological tests have been regarded as a traditional way to understand human motivation. However, advances in the study of brain activities using electroencephalography (EEG) are starting to offer alternatives. The first EEG was developed by Hans Berger, a German psychiatrist, in 1929 [12]. EEG technology exploits how the human brain works by measuring electrical impulses from neurons through the scalp. Currently, a wide range of EEG research has been conducted to diagnose mental illness, understand the functions of brain regions, read human minds and even do mind control [13]. Motivation measurement via EEG could be a useful approach because it provides objective information about human brain activities.

Overall, individual differences in motivation could explain why people act differently in the same situation, and which aspects of a game people with different motive profiles may find most engaging. Understanding and modeling player motivation helps us design entertaining games. Besides psychological tests, EEG technology could be an objective way to understand motivation during play without interrupting the game. Therefore, the issue of measuring player motivation using EEG is addressed in this thesis. Section 1.2 of this chapter overviews the basic content of this thesis and summarises the way we synthesise the research fields of psychological motivation, EEG and computer games. Section 1.3 proposes the research questions that are addressed in this thesis. The contributions and significance of this work are described in Section 1.4, followed by Section 1.5 which gives an overview of the remaining chapters of this thesis.

1.2 Thesis Summary

Motivation is defined as 'the cause of action' in psychological theory [14]. Motivation explains the reasons why individuals' behaviour is diverse in the same situation. Motivation in humans has been studied in broad fields (e.g. neuroscience, biological, and psychological theories) and can be divided into four categories: biological, cognitive, social and combined motivation theories and models [15]. Biological motivation theories, such as drive theory [16], motivational state theory [17] and arousal [18], explain behaviour in terms of biological drives and variables like hunger and thirst. In addition, cognitive motivation theories focus on goal-seeking behaviour like curiosity [19], operant theory [20], incentive [14], achievement [21] and intrinsic motivation [6]. They explain how consequences and expectations influence human behaviour according to the cost and benefits of each action. Social motivation theories discuss what individuals do when they are in contact with others. Theories include conformity [22], cultural effect [14] and evolution [23], and they describe individuals in situations ranging from small groups to larger societies, cultures and evolutionary systems. Combined motivation theories attempt to synthesise biological, cognitive and social motivation theories, for example, Maslow's

Hierarchy of needs [24].

To better understand player experience, player profiling is often developed from psychological theory. The study of motivation psychology provides us with insights into many areas of player experience. Examples of these insights include: how player personalities influence need, satisfaction and intrinsic motivations [25]; how intrinsic motivation (challenge, fantasy, and curiosity) impact game design [26]; how psychological needs (materialistic, power, affiliation, achievement, information and sensual) motivate players to play games [8]; how self-determination theory for autonomy, competence and relatedness predict enjoyment and future game play [27]; and how five user motivations (achievement, relationship, immersion, escapism and manipulation) change the way players play [7].

Due to the diversity of motivation types and underlying cognitive and biological processes, we limit our investigation in this thesis to a specific category of motivation theory: achievement, affiliation and power motivations, for understanding and modeling player motivation in computer games.

There are three reasons to justify this choice. First, these three motivations can be mapped with existing player types from the study of player experience in computer games, as described in Fig. 1.1. Secondly, these three motivations have been influential in the field of motivation psychology, forming the basis of a number of theories such as the three-need theory and three-factor theory (more details in Section 2.3). Finally, these three motivations underlie a wide range of behaviours including social, risk-taking and skill acquisition behaviour. These behaviours [28], in turn, can be linked to the players' emotion, risk and social attitude in strategic decision-making scenarios. These are readily detected using EEG. Therefore, we regard achievement, affiliation and power motivations as a promising starting point to study player motivation.

However, identifying a player's motive profile from data available during gameplay remains an open challenge. Game designers, academics, psychologists and neuroscientists have examined this issue from different perspectives, resulting in a range of

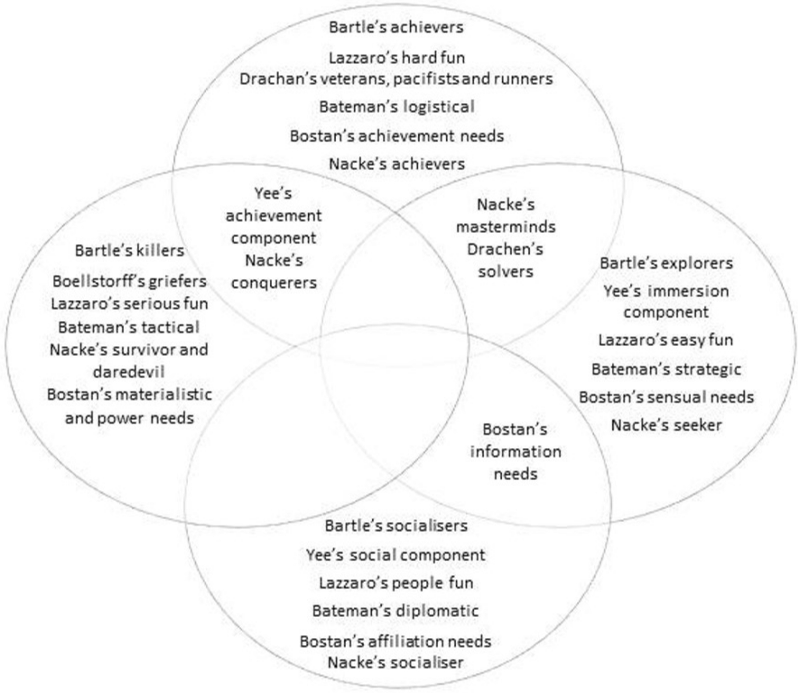


Figure 1.1: We categorise existing player types and player motivation studies into four groups, and identify areas of overlap between the groups.

different subjective and objective techniques for identifying player types and classifying player motivation. Subjective measures include questionnaires, the thematic apperception test (TAT) [29] and the multi-motive grid method (MMG) [30]. On the other hand, objective measures have been emerging in recent years, which involve behavioural analysis [31]. However, disagreement remains regarding the categories of player motivation that should be used and a real-time, objective measures for identifying the category that best describes a given player in a simulation environment.

Psychophysiological methods, in particular EEG, measure the neural oscillations of the central nervous system (CNS) and provide reliable, high time-resolution measurements of cognition [32–36] and emotion [37]. The literature shows that theta and gamma oscillations relate to memory [32], alpha band indicates attention [33,34] and alpha and theta bands are indicators of mental workload [35,36]. There are also related EEG studies concerning recognition of emotion. Frontal EEG asymmetry studies (especially in the alpha band) are found to differentiate valence of emotion [38], and it is hypothesised to reveal approach and withdrawal emotions [39]. Moreover, the gamma band is shown to be associated with negative valence [40] and can be used to classify positive and negative emotions [35, 41].

EEG measurement does not interfere with players while they are performing most tasks. The data mostly comes from involuntary processes, so it could be regarded as a promising way to understand player experience through measuring emotion, cognition and even motivation during gameplay. In recent studies, EEG technologies have facilitated the study of player experience modeling and game flow in computer game research [42–45], and they have promoted research applying brain computer interfaces (BCI) in computer games [46]. However, whether EEG can be regarded as an objective, game-independent technique to measure player motivations remains an open question.

According to psychological motivation theory, achievement, affiliation and power motivated individuals have different risk-taking behaviours, social attitudes and emotions, which have been studied in the EEG literature. Examples like pre-frontal alpha band [47], theta-beta ratio [48] and some event-related potentials (ERPs) [49, 50] indicate risk-taking attitudes; the mu band [51] and alpha band [52] reflect social attitudes. Based on the literature, we propose conceptual models linking player motivation and EEG, providing us with the possibility of learning about human motivation from EEG signals. In order to evoke the characteristics of different motivations in this thesis, an abstract game is designed to reflect risk-taking and social attitudes in a strategic decision-making scenario. The framework that links motivation theory, EEG technology and computer games in this thesis is depicted in Fig. 1.2.

Overall, modeling player motivation complements and extends research on game flow, which helps us design entertaining games. Current player models focus on emotion, cognition and behaviour, but motive profiles have not been fully studied. The study of player motive profiles should facilitate adaptive and interactive game design that satisfies a broader range of player needs. The advantage of using EEG

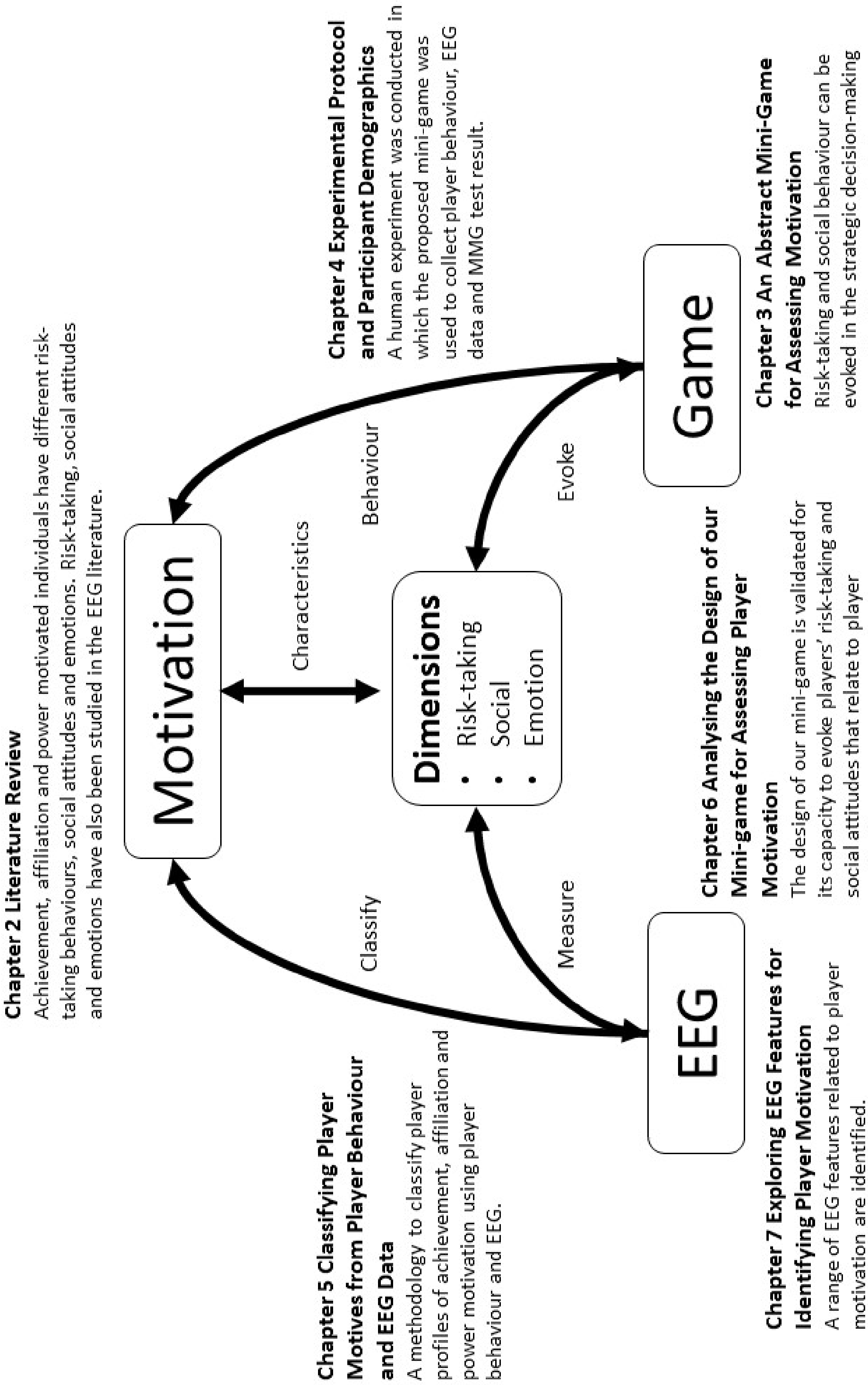


Figure 1.2: Overview of the connecting framework for the thesis. Psychological motivation theory, EEG measurement and a game scenario are linked by the three dimensions of achievement, affiliation and power: risk-taking, social attitudes and emotion.

as a source of information while performing a task is that it does not interfere with classic control devices such as joysticks, keyboard, mouse, gesture and voice. Moreover, the continuous nature of EEG signals offers an opportunity for real-time data analysis and profiling of the user in a system. Therefore, we consider EEG technology to be a promising approach for measuring players' motivation profiles of achievement, affiliation and power during an abstract decision-making scenario.

1.3 Research Challenges and Questions

The aim of this thesis is to develop methodologies to assess achievement, affiliation and power motivation profiles of computer game players from EEG signals while they are engaged in a game. In order to achieve the goal, the following key challenges are addressed in this thesis:

Challenge 1 A crucial part of neuroscience research is the design of sound experimental scenarios [45]. It is important to have an appropriate game protocol to measure player motivation profiles through EEG technology. Virtual worlds and games are complex because of the topographic diversity of virtual worlds, the various kinds of tasks and demographic diversity of players. Therefore, the reactions or motivations of players may be confounded by variables other than the one we need to measure. The challenge, therefore, is to design a game that is complex enough to evoke the characteristics of different motivations: in this case risk-taking, social attitude and emotion, but simple enough to control for other variables. Chapter 3 of this thesis addresses this challenge by designing a minimalist computer game scenario for this purpose. The game is analysed in Chapter 6.

Challenge 2 The second challenge is the synthetic analysis of subjective and objective motivation measures. Even though subjective methods can be difficult, we still need to take them into account when identifying individual motivation as it comes from the source of participants. Thus it is necessary to contrast conclusions from both subjective and objective approaches, because subjective methods present the self-awareness of participants about their motivation and game preferences. This research challenge is addressed in Chapter 5.

Challenge 3 EEG measurements can be recorded automatically and continually (real-time) without interrupting the experiments and being influenced by participants' natural behaviour. The research challenge of EEG data analysis is first to decide on suitable signal processing methods. Different signal processing and data mining methods have been employed during three steps of EEG data analysis: feature extraction, feature selection and feature classification. In order to measure player motive types, an appropriate methodology should be identified at the data analysis stage. This challenge is addressed in Chapter 5.

Challenge 4 The other research challenge associated with EEG measurement is to select EEG features for motivation recognition and identify the responsible brain regions. Neuroscience papers of emotion recognition, risk-taking and social attitude point out a number of EEG features. However, it is hard to identify which ones are responsible for player motivation classification. The possible solution is to use suitable feature selection algorithms to choose the most relevant EEG features, after obtaining the EEG data. This challenge will be addressed in Chapter 7.

According to the above research challenges, this thesis attempts to answer the following research questions:

- **Question 1** How to design a game scenario that is complex enough to evoke the characteristics of different motivations (risk-taking, social and emotion), but simple enough to control other variables?
- **Question 2** Are there any differences between subjective, objective and the proposed EEG-based measures when profiling achievement, affiliation and power motivation?

- **Question 3** What is the suitable signal processing procedure to analyse EEG data in order to measure player motivation?
- **Question 4** What are relevant EEG features for motivation recognition and the meta-cognitive states (risk-taking and social)?

Question 1 addresses the game design to support the use of EEG for profiling achievement, affiliation and power motivation. Question 1 is answered in Chapter 3 by proposing the design of our mini-game and in Chapter 6 by examining the design of the mini-game for assessing player motivation. Question 2 is addressed in Chapter 4 by collecting data on player behaviour, EEG data and psychological test data in the experiment and in Chapter 5 by comparing the performance of different approaches for assessing motivation.

Question 3 focuses on the use of EEG data to classify the player profiles of achievement, affiliation and power motivation. It is answered in Chapter 5 in which a series of EEG signal processing methods are presented. Question 4 examines EEG features to identify mental states that are indicators of achievement, affiliation and power motivation. Questions 4 is addressed in Chapter 7 by identifying EEG features for player motivation.

1.4 Contributions and Significance

By addressing the research challenges and answering the research questions of this thesis, we make the following contributions:

Contribution 1 A game scenario is designed for EEG profiling of achievement, affiliation and power motivation. To examine the different strategic decision-making behaviours (risk and social factors), the game scenario employs the prisoner's dilemma game as the game mechanics. Four non-player characters with different play strategies are designed, and players choose their own goals to play the game for friends or fortune. Non-player characters have two features, money and satisfaction. Players first play with the characters individually to trade-off money and satisfaction, and then team-up with their social network to play for fun. The way players play the game reveals their risk-taking and social behaviour. The mini-game proposed in this thesis provides a scenario for exploring human strategic decision-making behaviours, which further identifies their dominant motivations according to the psychological theory. This thesis first uses the game to investigate human motivation, which has implications for game design, player profiling and artificial intelligence in the future. The interactions between human players and non-player characters have the potential to provide insights into human factors in human-machine interactions and human-machine teaming.

Contribution 2 A human experiment is conducted to collect data using the game scenario. In order to engage subjects into the game and collect relevant data, the game is embedded in a multi-stage experimental protocol that begins with a tutorial, is followed by a play phase and finishes with an existing semi-projective questionnaire, the MMG. An in-game event coding system is designed to label EEG segments that can be used for further data analysis. Three kinds of data are collected during the experiment: player behaviour data, EEG data and MMG data.

Contribution 3 Methods for analyzing the EEG signal for classification of achievement, affiliation and power motivation are proposed. The EEG signal processing begins with the pre-processing procedure, artifact removal, epoch segmentation and then uses complex wavelet analysis to extract time-frequency features into different frequency bands. The features are then selected using a correlation-based feature subset evaluation method, and finally input to the k-nearest neighbours algorithm to classify player profiles of achievement, affiliation and power motivation, in terms of three different labelling schemes. By comparing motivation classification using player behaviour and EEG signals, the hypothesis that EEG technology can be a promising approach for identifying player motive profiles is validated.

Contribution 4 Based on the literature review on psychological motivation theory, the proposed player types in computer games and EEG technology, conceptual models that link player motivation profiles and EEG are proposed. We examine the design of the game for assessing characteristics of achievement, affiliation and power motivation: risk-taking, social and emotion by validating EEG features in the conceptual model. Finally, we explore possible EEG features and brain regions to assess player motivation using a correlation-based features subset evaluation method. The significance of this contribution is to identify the critical frequency bands and brain regions corresponding to the mental states that are indicators of achievement, affiliation and power motivation. These EEG indicators could be utilised in future human-machine interaction, simulation environments for training, game design and a variety of artificial intelligence studies.

1.5 Thesis Overview

The rest of this thesis is organd as follows: Chapter 2 reviews background works on three fields: motivation psychology, player profiling in computer games and electroencephalography. By reviewing relevant works, we saw that achievement, affiliation and power motivated players have different characteristics of risk-taking, social attitudes and emotion. These characteristics may be revealed in strategic decision-making behaviour and can be revealed by EEG technology. Thus we proposed several conceptual models, which were used to design an abstract mini-game, described in Chapter 3. In Chapter 4, the mini-game was embedded in an experimental protocol to collect player behaviour and EEG data from the game. Motivation data from a multi-motive grid test was also collected in the experiment, which is regarded as a ground truth to identify the relationships between player behaviour, motivation and EEG data. In Chapter 5, we compared classification accuracies between player behaviour and EEG data to assess motivation. Further, in Chapter 6 we examined, in more detail, the effectiveness of the game design using player behaviour and EEG features at specific points in the game. Finally in Chapter 7, we focused on EEG signals, to validate the conceptual models that originated from literature review in Chapter 2. We also performed a more comprehensive exploration of a range of EEG features for identifying player motivation in the mini-game. Conclusions are drawn in Chapter 8. The content of each chapter is summarised below:

Chapter 2 This chapter reviews relevant literature on achievement, affiliation and power motivation, player motivation types, and EEG, providing evidence for the conceptual models that identify the possibilities for measuring player motivation using EEG signals. It begins with a literature review on psychological motivation theory of achievement, affiliation and power, and identifies the three characteristics of these motivations: risk-taking, social and emotion. Further, it focuses on the theoretical basis of applications of EEG to measure cognitive characteristics relevant to player motivation types.

Chapter 3 This chapter presents the design of a two phase mini-game for assessing achievement, affiliation and power motivation. Inspired by the three key cognitive characteristics that emerged from the review in Chapter 2: risk-taking, social factors and emotion, we justified the prisoner's dilemma as the scenario to reveal human strategic decision-making behaviours. Moreover, the design of the game's non-player characters, storyline, mechanics, world, and gameplay are described in this chapter. Several simulations were conducted to the game mechanics as a preliminary indicator that the game can be played in different ways to reveal player motivations.

Chapter 4 This chapter presents the experimental setup used in the remainder of the thesis. It covers the way the game was embedded in a multi-stage experimental protocol that included a tutorial, play phase and existing semi-projective questionnaire, the MMG. More specifically, it describes the experimental environment, procedure and particularly the setup for EEG signal collection. The player behaviour data, EEG data and MMG data were collected in this experiment and the data collection methodology is illustrated in this chapter.

Chapter 5 This chapter presents a methodology for classifying player profiles of achievement, affiliation and power motivation using player behaviour and EEG signals in terms of the relative strengths of the hope and fear components of each motive. It first proposes three subject labelling schemes using MMG test output. This is followed by the workflow for EEG signal processing, including the signal pre-processing, feature extraction, feature selection and classification procedures. We experimented with three subject labelling schemes to support classification. For the results, we demonstrated that EEG profiling of achievement, affiliation and power motivation is more accurate than profiling from player behaviour. Moreover, we identified which phases of the mini-game support the most effective EEG profiling.

Chapter 6 This chapter validates the design of our mini-game to evoke risk-taking and social attitudes that ultimately relate to player motive profiles. Non-player characters (NPCs) proposed in the game have a money dimension, satisfaction dimension and various play behaviours. We analysed the NPCs from the perspective of player behaviours and EEG signals. Results demonstrate the effectiveness of using the money and satisfaction dimensions of NPCs for evoking risk-taking and social attitudes from EEG results. Also, the behaviour of different NPCs, as well as the individual play and social network play, are examined for their relevance as mental indicators of player motivation.

Chapter 7 This chapter presents an investigation of EEG features for assessing player motivation in different phases of our mini-game. First, conceptual models that link motivation theory to mental states are identified using EEG signals collected from the game. This study focuses on finding relationships between EEG features and motivation variables from the MMG test. Furthermore, a wider range of EEG features are explored than in the existing literature. We studied temporal, spectral, time-frequency and asymmetry features to identify related brain regions and frequency bands for assessing player motivation. The most effective features are selected using machine learning methods. These results, in turn, support the application of EEG to identify player motivation in this game.

Chapter 8 This chapter summarises key findings of this thesis and identifies directions for future work. The main contribution and findings of this thesis are to identify the potential for using EEG to identify achievement, affiliation and power motivation in an abstract game scenario. As this is the first attempt to apply EEG to motivation recognition in a computer game, further investigations are required to improve its performance. Specific directions for future investigation are discussed in this chapter.

Appendix A This section presents the tutorial booklet of our mini-game. This booklet is used in the experiment to train players in the tutorial phase, and instruct players in the game phase.

Appendix B An experiment that compares different classification techniques is discussed in this section. The performance of four different classification techniques (C4.5, KNN, Random forest and naive bayes) are compared using player behaviour and EEG data.

Appendix C Different artifact removal techniques are compared in this section. To obtain the optimal EEG signals for data analysis, those classic artifact removal methods, FASTER, ADJUST and a proposed manual method are performed in an experiment.

Appendix D This section displays the numerical results that support the conclusions drawn regarding the ability of NPCs to predict risk-taking and social attitudes in Chapter 6.

Appendix E This section presents an experiment that compares different feature selection methods. Three feature selection methods (chi-squared attribute evaluation, correlation subset evaluation and wrapper subset evaluation) are compared using EEG signals from the two play phases of our game.

Chapter 2

Literature Review

The work, reported in this chapter, has been partially published in the following article:

Xuejie Liu, Kathryn Merrick and Hussein Abbass (2017), *Towards Electroencephalographic Profiling of Player Motivation: A Survey.* IEEE Transactions on Cognitive and Development System, vol. 10, No. 3, pp. 499-513.

2.1 Introduction

A key early concept for understanding players is the concept of game flow. A model of flow was first proposed by Csikszentmihalyi [1], who identified eight characteristics of flow: skill-oriented challenge, concentration on the task, clear goals, explicit feedback, sense of control, transformation of time, loss of self-consciousness and the merging of action and awareness [53]. The flow model identifies a region of 'optimal experience' of a game, where tasks are neither boring nor anxiety inducing (see Fig. 2.1). In other words, flow occurs when players perceive challenges that perfectly match their abilities [54, 55]. If the challenge of a game is beyond the player's ability, the game begins to generate anxiety. In contrast, if game tasks become easy for players, they tend to feel bored and may stop playing the game [56]. Game designers recognise that different players have various skills and expectations of challenges for games. To keep all players in the flow zone for the duration of the game, techniques such as dynamic difficulty adjustment (DDA) [2,57] have been proposed to permit games to adapt their challenges dynamically to suit individual needs, skills or experience levels.

In recent years, the study of flow has been complemented by studies in motivation psychology. Examples of these insights include: how player personalities influence the need for satisfaction and intrinsic motivation [25]; how intrinsic motivation (challenge, fantasy, and curiosity) impact game design [26]; how psychological needs (materialistic, power, affiliation, achievement, information and sensual) motivate players to play games [8]; how self-determination theory can predict enjoyment and future game play [27]; and how user motivations change the way players play [7]. This thesis builds specifically on this area of work, with the aim of developing objective ways to assess player motivation using electroencephalography. The thesis thus relies on background work in three fields: motivation psychology, player profiling in computer games and electroencephalography. Accordingly this chapter is arranged in three sections to review relevant work from each of these fields. Section 2.2 reviews literature on player profiling in computer games and illustrates how the similarities between well accepted player types and achievement, affiliation and power motivation justify our focus on this area of motivation psychology. Section 2.3 introduces the specific branch of motivation theory investigated in this thesis. Section 2.4 reviews the most relevant work using electroencephalography that we build on to inform the studies in this thesis.

2.2 Computer Games and Player Types

Several scholars have applied motivation theory to game contexts. Early work by Malone [58] explored the role of motivation in making games captivating, especially how intrinsic motivations make games fun. Three categories of motivations were synthesised in his study: challenge, fantasy and curiosity. Challenge refers to goals with uncertain outcomes, variable difficulty level and multiple level goals, as ways of making games challenging. The inclusion of fantasy is claimed to provide cognitive and emotional advantages to game environments.

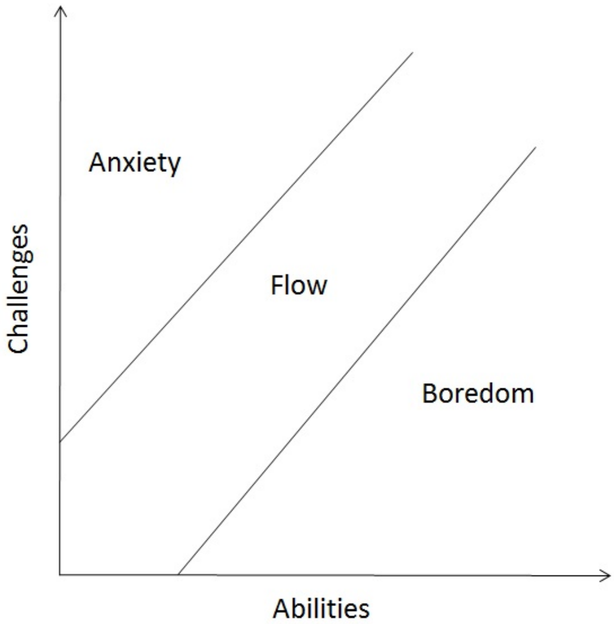


Figure 2.1: Graphical representation of the 'flow zone'

Curiosity is related to sensory curiosity that relies on audio and visual effects, in addition to cognitive awareness of self-knowledge structures that are incomplete and inconsistent. The game environment can evoke curiosity by providing an optimal level of informational complexity. Bostan et al. [8] extracted a broader range of game motivations from basic human needs in six categories: materialism, power, affiliation, achievement, information and sensual needs.

Specifically, power needs represent the will to arouse strong emotions in other people and to be in charge; affiliation needs serve as the incentive to build and maintain a positive social relationship with others; achievement needs stand for the desire to achieve success. Each motivation has appropriate desires, effects, actions, emotions, personality traits and relationships with other motivations. Bostan claimed that the motives of game players originate in the relationship between the psychological needs of players and game situations provided by a virtual world. He takes *Fallout 3* as an example and proposes game statistics, such as action points, carry weight, critical changes and so on, which are relevant to motivational variables [8].

Ryan et al. applied self-determination theory (SDT) to investigate motivations for computer game play via four experimental studies [27]. SDT [6] is employed to address both intrinsic and extrinsic motives in game contexts, and particularly focuses on psychological needs for autonomy, competence and presence.

In Chapter 1, Fig. 1.1 grouped a number of well-known player types [3,4,7,26,59] alongside the player motivation models discussed above. When viewed in this way, it becomes apparent that a subset of these theories align naturally with conceptual models from motivation psychology, such as *three needs theory* [60] and *three factor theory* [61]. We highlight this in Tab. 2.1. The next section introduces achievement, affiliation and power motivation in more detail from the motivation psychology perspective.

Table 2.1: Mapping a subset of player type literature to achievement, affiliation and power motivation

Player type	***Achievement***	***Affiliation***	***Power***
Bartle [3]	Achiever	Socialiser	Killer
Drachen et al. [59]	Veterans; Runners; Pacifists		
Lazzaro [4]	Hard fun	People fun	Serious fun
Yee [7]	Achievement	Social	Immersion
Bostan [8]	Achievement	Affiliation	Power; materialism
Nacke et al. [26]	Achievers	Socialiser	Survivor; daredevil
Ryan et al. [27]	Competence		
Boellstorff [62]			Griefers
Bateman et al. [63]	Logistical	Diplomatic	Tactical

2.3 Motivation Theory

The field of motivation is broad, including neuroscience, biological, and psychological theories [15]. Furthermore, an individual's motivation may be influenced by personal factors or contextual factors [28]. The diversity of motivation types and underlying cognitive and biological processes thus requires that we limit our initial investigation to a specific category of motivation theory. Following the reasoning in the previous section, we chose achievement, affiliation and power motivation for a variety of reasons. On the one hand, these three motivations can be related to existing player types from the study of player experience in computer games [64].

On the other hand, these motives have been influential in the field of motivation psychology, forming the basis of a number theories such as the three needs theory [60] and three factor theory [61]. They underlie a wide range of behaviours including social, risk-taking and skill acquisition behaviours. Furthermore, these behaviours, in turn, can be linked to emotion, risk and social attitude, which we will see in Section 2.4 are characteristics that have been studied in the electroencephalography (EEG) literature. They thus make a feasible starting point for development of techniques for distinguishing motivation using EEG. To facilitate this, the following three sections introduce each of these motivation theories from the perspectives of emotion, risk-taking and social attitude. We conclude this section with a study of existing techniques for measuring motivation in Section 2.3.4.

2.3.1 Achievement Motivation

Achievement motivation is defined as an individual's desire to strive for excellence and to increase their competence. Achievement motivation develops in achievement-related tasks, activities and skills [28]. Standards of excellence can be classified according to personal and social aspects. From the personal perspective (mastery oriented), people compare their current performance with their own experience instead of with that of others. Thus self-evaluatory emotion is involved in this process. Joy and sadness accompany the acquisition or loss of a desired objective [28]. Furthermore, pride and shame, also linked to dominance and submission, are understood to be expressions of the evaluation of one's competence against a standard of excellence. The emotions relevant to achievement motivation are summarised in Tab. 2.2 (column 2).

Another aspect of achievement motivation that has been considered is in the context of risk-taking. One model of ris-taking in achievement motivation is Atkinson's Risk-Taking Model (RTM) [65]. The RTM aims to predict individual preferences for accepting difficult goals by combining components for conflicting desires to approach success and avoid failure. Such an approach is modelled by variables for probability of success (equated with difficulty); incentive for success (equated with value of success); and strength of motivation to approach success. Failure avoidance is modelled by variables for probability of failure; incentive for avoiding failure (equated with cost of failure); and strength of motivation to avoid failure. The general trends described by the RTM have been observed in experimental settings in humans [65, 66] and the RTM has been correspondingly influential and successful in aiding the understanding of achievement motivation in humans. From a social perspective, studies have shown that achievement motivated individuals may prefer to work alone and may prefer goals of moderate risk [28]. These characteristics are summarised in Tab. 2.2 (column 3 and column 4).

Table 2.2: Characteristics of emotion, social attitude and risk-taking that may be observed in individuals with a given dominant motivation

Motivations	***Emotion***	***Social attitude***	***Risk-taking behaviour***
Achievement	Joy and sadness; pride and shame	Often likes to work alone, but likes regular feedback	Achievement-motivated participants prefer moderately challenging goals, are willing to take calculated risks
Affiliation	Trust; empathy; love; liking	Wants to belong to a group; wants to be liked; Prefers collaboration over competition	Affiliation-motivated participants select goals with a higher probability of success (or low risk)
Power	The positive emotion; a sense of control	Wants to control and influence others; likes to win; likes competition; likes status and recognition	Power-motivated participants select high risk tasks

2.3.2 Affiliation Motivation

Like achievement motivation, affiliation motivation has also been considered from the perspective of emotion, risk-taking and social attitude. The key difference is in the dominance of these factors within an individual. Affiliation motivation is a desire to seek and maintain contact with strangers or little known individuals [28]. Affiliation motivated individuals enjoy forming friendships and associations. They want to greet, join groups, please others, and cooperate with others. The emotions associated with affiliation motivation are trust, empathy, love and liking [28], which are shown in Tab. 2.2 (column 2). The influence of affiliation on social attitude is summarised in column 3.

There are two sides of affiliation motivation: hope of affiliation and fear of rejection. Fear of rejection triggers caution and sensitivity when people meet strangers, whereas hope of affiliation encourages us to approach strangers and become familiar with them. When unfamiliar people interact, they first experience hope of affiliation. As the relationship becomes closer, fear of rejection increases because rejection would be more painful.

As for risk-taking behaviour, affiliation motivated individuals prefer low-risk goals, and may avoid public competition and conflict that may lead to the acquisition of resources that are desirable to others [28]. This is summarised in Tab. 2.2 (column 4).

2.3.3 Power Motivation

Power motivation can be described as an asymmetric relationship between two individuals, in terms of social competence, access to resources or social status [28]. Like affiliation motivation, there are also two conflicting aspects of power motivation: hope for power and fear of loss of power. Fear of power, resulting in a desire to avoid power, may be the result of fear of a failed power-play, or fear of being trumped by another. Some analysis shows that the expression of power is linked to positive emotional experience, and participants' sense of control plays a major role in power behaviour [28], (see Tab. 2.2 (column 2)).

Like affiliation motivation, power motivation can be considered with respect to incentive, probability of success and risk. Specifically, there is evidence that the strength of satisfaction of the power motive depends solely on incentive. That is, power motivated individuals do not focus as strongly on the probability of success of achieving a goal [66]. Power motivated individuals tend to prefer high risk or high payoff goals because their success is likely to give them access to desirable resources or social status [28]. Their social attitudes and risk-taking behaviour are depicted in Tab. 2.2, column 3 and column 4.

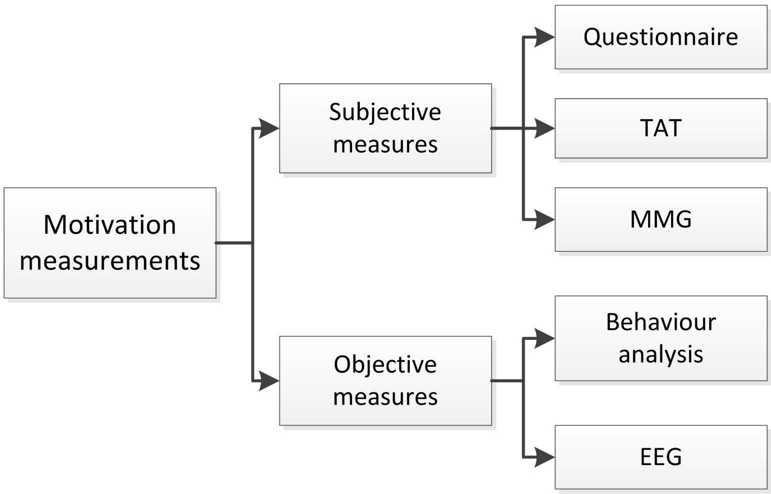


Figure 2.2: Subjective and objective measurements of motivations

2.3.4 Measuring Motivation

Techniques for measuring motivation can be classified as either subjective or objective as shown in Fig. 2.2. Subjective measures include questionnaires, the thematic apperception test (TAT) and the multi-motive grid method (MMG). On the other hand, objective measures, which have been emerging in recent years, involve behaviour analysis. These four traditional motivation measures are discussed in this section, together with their strengths and weaknesses. The fifth potential form of measurement, shown in Fig. 2.2 is EEG, and is discussed in Section 2.4.

2.3.4.1 Questionnaires

The simplest method of measuring human motivation is to ask subjects what their motives are, what they prefer to do under certain circumstances, or what their goals are. Self-report or questionnaires are based on the assumption that subjects are aware of the causes of their behaviour. However, people are often not conscious of their motivations, so the use of questionnaires for motivation measurements can be difficult.

Subsequently, an alternative test, the Cezarec Marks Personal Scheme (CMPS), has also been proposed and compared with the TAT for measuring achievement [67].

The CMPS includes 11 sub-scales, of which achievement is one. Each sub-scale has 15 questions. The subject has to answer yes or no. Scoring should consider age, sex and which group the subject belongs to, according to the manual. However, results indicated that the TAT cannot be replaced by CMPS. The reason behind this is that a person may self-report they are interested in achievement, but actually lack the motive to do so.

2.3.4.2 The thematic apperception test

The thematic apperception test (TAT) is a projective measure that requires subjects to write a series of stories about several motive-related pictures. In the TAT, participants are instructed to write a short story about each picture, explaining the situation in the picture, what the people are thinking and feeling, and even how the story will end in their imagination. The content of their story is then evaluated to identify the motive activated.

The TAT coding system of achievement motivation scores is as follows: achievement-related (score: +1) for

- explicit reference to a standard of excellence;
- reference to a truly exceptional performance outcome;
- reference to long-term achievement goals.

Achievement-neutral (score: 0) if

- none of the above criteria were satisfied and any work mentioned was thus of a routine nature.

Achievement-unrelated (score: -1) if

- the story contained only imagery relating to other motives.

In conclusion, a typical TAT begins by determining the context in which the test is embedded; then giving the instructions and administering the test. This may be in a group setting or in a one-on-one setting, in writing or as an oral report. After the achievement-related content of pictures is identified, a coding system is used to analyse the content of the story [68, 69]. In particular, Schultheiss et al. described a step-by-step guide for measuring motivations and the use of a coding system in detail, which is a useful manual for motivation assessments [70].

Heckhausen developed a TAT technique to measure both hope for success (HE) and fear of failure (FM) using picture stories. Success-motivated participants (HE) favoured goals that slightly exceeded their previous level of performance. Failure-motivated participants, in contrast, fell into two groups: some set themselves excessively low goals, while others set themselves unrealistically high targets. Correlation analysis shows that the two motives are mutually independent, indicating that some people have both hope for success and fear of failure [28].

Some scholars criticise TATs as time-consuming, subjective and difficult to interpret [67, 71]. Moreover, some researchers showed that questionnaires and TAT measures are virtually uncorrelated [72]. On the other hand, McClelland, Atkinson and their colleagues assert that TATs predict long-term and real-world behaviour whereas questionnaires are better at predicting choices and attitudes [73–75]. Furthermore, they argue that TATs and questionnaires measure distinct aspects of motivation. TATs measure implicit motives that have been labeled as needs for achievement (nAch), power (nPow) and affiliation (nAff). The other category of personal motivations called self-attributed motives, that usually refer to values, such as self-attributed achievement (sanAch), self-attributed power (sanPow) and self-attributed affiliation (sanAff), are often measured by self-report methods. There are various differences between implicit motives and self-attributed motives [72].

Self-report and TAT measures have been compared based on achievement and affiliation motives [76]. For the achievement motive, there are no differences between questionnaires and TAT measures. TAT measures performed better than questionnaires for males and but not for females when measuring affiliation motives [76]. Splangler later used two meta-analyses of 105 randomly selected articles to find relationships between questionnaires and TAT for achievement [72]. Results demonstrated that, on average, TAT-based correlation is larger than questionnaire-based correlation, with TAT more positive with intrinsic, task-related and achievement incentive, while questionnaires are more related to external and social achievement incentive.

2.3.4.3 The grid method

Despite the objective coding system, the TAT method is sensitive to subjective influence. Schmalt developed the achievement motive grid (AM Grid), which combines the TAT method with a questionnaire [77]. Rather than writing stories, a set of statements is appended to each picture. Participants are required to check 18 statements with 18 pictures, and to say whether they both express the same situation. Three different motives are distinguished as HS (the conceptual equivalent of the TAT success motive), FF-1 (active failure avoidance and items reflecting a low self-concept of ability) and FF-2 (fear of failure and its potential social consequences). Three types of grid methods have been developed for achievement, affiliation and power motives respectively. Each motive is measured in terms of its approach and avoidance tendencies.

Sokolowski et al. [30] developed the multi-motive grid (MMG) that aims to measure three motives by combining pictures and statements into one single measure. A set of pictures reflecting a set of achievement, affiliation and power invoking situations is presented, together with a group of statements. A sample picture and statements from a commercially available version of the MMG are shown in Fig. 2.3. Six motive scores are generated from the test: hope of success (HE) and fear of failure (FM), hope of affiliation (HA) and fear of rejection (FZ), and hope of control (HK) and fear of loss of control (FK). The full set of statements and the mapping between motive scores, achivement, affiliation and power are shown in Tab.. 2.3

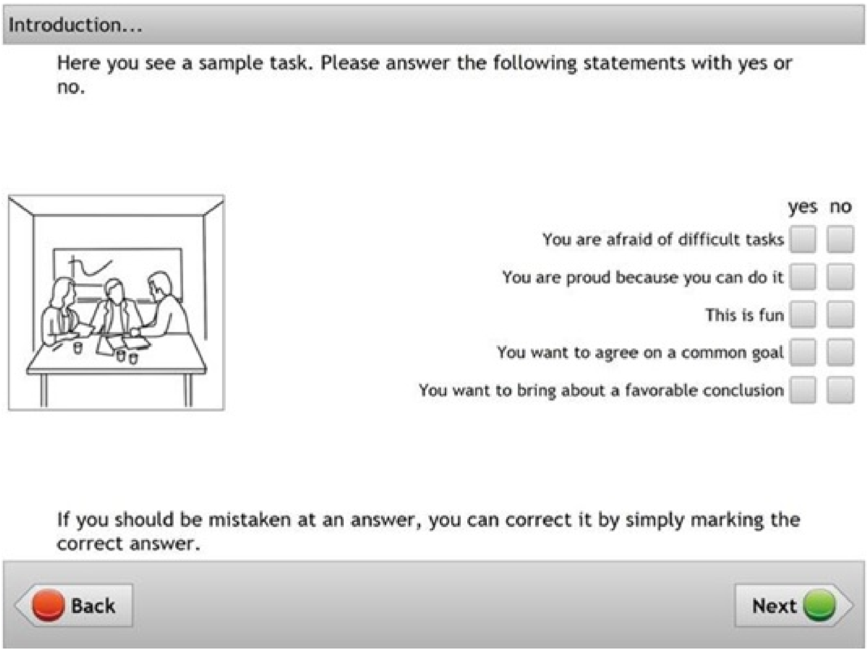


Figure 2.3: An example picture and statements from a commercially available MMG test (https://www.schuhfried.com/)

The results from MMG can be analysed in various ways. Firstly, individual features can be analysed for a given individual as 'average', 'above average' or 'below average'. An example is shown in Fig. 2.4. Alternatively, results of factor analysis in Sokolowski's article [30] suggest three factors that comprise a general fear factor (FM, FK, FZ), a factor combining the hope components of achievement and power (HE and HK), and the third factor of hope for affiliation, (HA). A third approach is to divide participants into four groups according to four possible combinations of high and low levels of hope and fear. High hope and low fear (H-L) or low hope and high fear (L-H) (Situations 1 or 4 respectively in Fig. 2.5) are indicators of motive dominance. High hope and fear (H-H; Situation 2) results in approach avoidance conflict and thus ambivalence in connection with the particular motive. Low hope and low fear (L-L; Situation 3) are expressed as a low level of spontaneous interest in a particular motive goal. This thesis uses the first and third of these approaches in Chapter 5 to label subjects for classification from EEG data.

Table 2.3: The 12 statements of a commercially available MMG (https://www.schuhfried.com/).

Statement	*Affiliation*	*Achievement*	*Power*
1. You are glad you have met	HA1		
2. You fear to lose social acceptance			FK1
3. You think you can do it		HE1	
4. In this situation you could easily be rejected by others	FZ1		
5. You think of abilities you do not have		FM1	
6. You fear the power of others			FK2
7. You are proud because you can do it		HE2	
8. You fear to be boring	FZ2		
9. You prefer not to deal with difficult tasks straight away			HK1
10. You would like to have an influence yourself		FM2	
11. You hope to get closer to the other one by taking the initiative	HA2		
12. This could improve your social acceptance			HK2

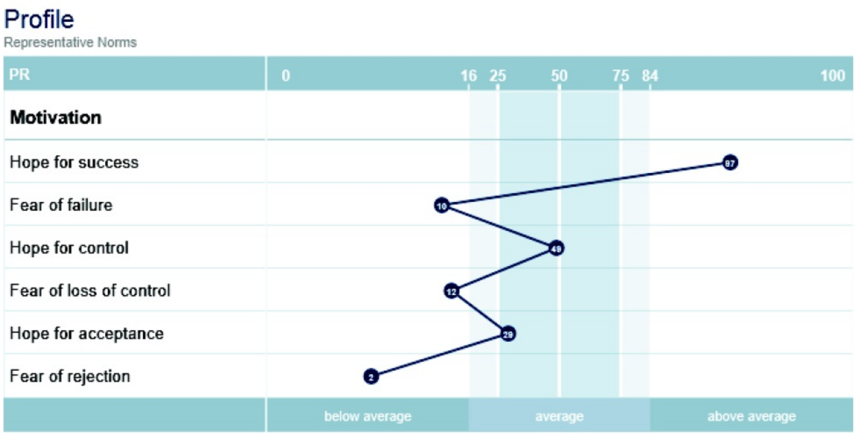


Figure 2.4: An example intepretation of MMG results as ‘average’, ‘above average’ or ‘below average’. (https://www.schuhfried.com/)

2.3.4.4 Behaviour analysis

Harrell et al. came up with an alternative approach to measure achievement, affiliation and power motives [31]. This method observes subjects’ decision-making behaviour when facing a choice of jobs, to determine how they weight achievement, affiliation and power. Subjects were informed that all other factors associated with jobs are identical except three key activities used to identify motives. These three activities are: establishing and maintaining friendly relationships with others to detect affiliation motivation, influencing thoughts or activities of individuals to detect power motivation, and accomplishing difficult goals and receiving regular feedback to detect achievement motivation. These three activities are carried out in various jobs with different frequencies, like ‘rarely’, ‘fairly often’ and ‘very often’. The

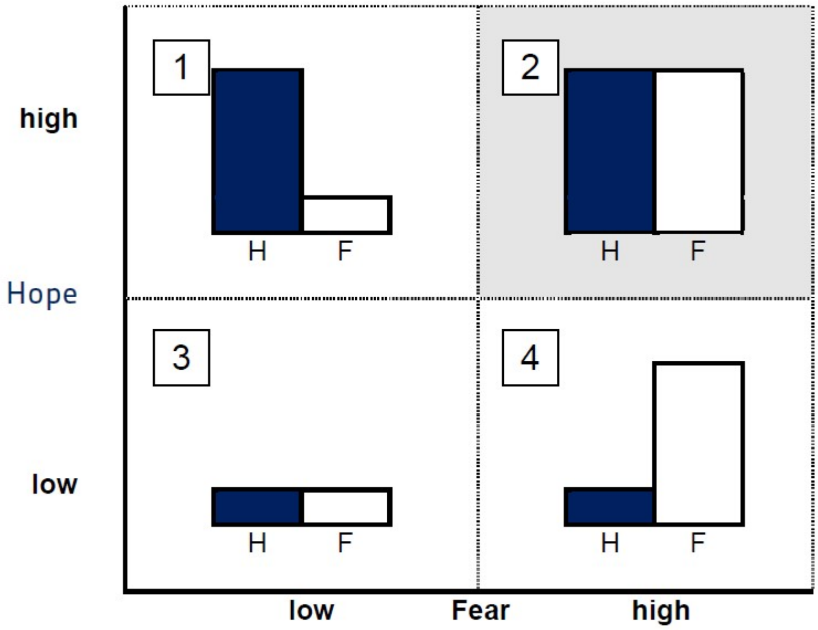


Figure 2.5: Interpretation of MMG results in four situations (applicable to each of achievement, affiliation and power). Situation 1 (H-H) is high hope and low fear for a motivation; Situation 2 (H-H) is high hope and high fear; Situation 3 (L-L) is low hope and low fear; Situation 4 (L-H) is low hope and high fear. (https://www.schuhfried.com/

definition of the three activities is consistent with incentive motivation theory.

In conclusion, although various motivation measurements have been proposed, there is no general agreement on how best way to measure motivation. In addition, the approaches described above cannot be conducted during a task without interrupting it. Therefore, an emerging technique that could be adopted as a promising and objective indicator of motivation measurement, electroencephalography, will be considered and examined in the next section.

2.4 Electroencephalography as an Approach to Measuring Motivation

Electroencephalography (EEG), detection of electrical activity in the brain, has been widely used in neuroscience and brain computer interfaces (BCI) [13, 78, 79], due to its low-cost, portability and non-invasiveness. EEG indicators are neither affected by participants' answering styles nor by observer bias [45]. Combined with other approaches (e.g. questionnaires and gameplay metrics), the EEG method, as an objective indicator for motivation, could add significant accuracy and convenience to the study of motivation.

The advantage of EEG as a source of information is that it does not interfere with classic control devices, such as joysticks, keyboard, mouse, gesture, and voice. Moreover, the continuous nature of EEG signals offers an opportunity for real-time data analysis and profiling of the user of a system.

The above argument holds also for psychophysiological data in general. For example, skin conductance and heart rate variability can be analysed continuously and in real-time as well. However, EEG signals are much richer in their contents; thanks to the distributed nature of human mental processing.

In general, to identify mental states from EEG, three types of information are frequently used: frequency data (oscillations at a similar frequency), temporal information (event related potentials, positive and negative peaks) and spatial data (position of the electrodes) [80]. In addition, various groups of features can be extracted from EEG signals: signal power features, statistical features, morphological features, time-frequency features and connectivity metrics [81–83]. Multiple machine learning techniques including the k-nearest neighbour (KNN) algorithm, multilayer perceptrons and support vector machines [84], fuzzy logic approaches [85], graph regularised extreme learning machines (GELM) [86], a linear dynamic system based feature smoothing and manifold learning [87], deep belief network (DBN), connectivity mask [82], linear discriminant function analysis (lDFA) and quadratic discriminant function analysis (qDFA) [35] have been applied to differentiate between and recognise discrete stimuli in different fields of research.

There are limited EEG papers focusing on measuring achievement, affiliation and power motivations. We seek to measure these three specific motivation profiles through their dimensions of emotion, risk-taking and social attitude. In this section, we outline existing EEG studies of emotion, risk-taking, and social attitude. We detail the corresponding data analysis methods together with EEG features, activating brain regions and experimental scenario.

2.4.1 Emotion Recognition

Different definitions of emotion have been proposed by researchers. The first type assumes that complex emotions are based on a set of basic emotions such as anger, fear, sadness, happiness, or surprise [88]. The second approach is a two-dimensional scale based on a valence-arousal coordinate system, called the circumplex model [89].

The circumplex model, a basic theory of emotion, is based on two axes, one for valence (unpleasant to pleasant) and the other for arousal (activation to deactivation). The model is shown in Fig. 2.6 [90]. Almost every emotion can be positioned according to these two dimensions. Each emotion also has several common characteristics: rapid onset, short duration, unbidden occurrence, automatic appraisal and coherence among responses [88]. In addition, emotions are driven by two motivational systems. Positive emotion is motivated by approach motive and negative emotion is consistent with withdrawal motivation [91].

2.4.1.1 Experimental Scenarios

Chanel et al. firstly verified the existence of three emotional states, boredom, engagement, and anxiety in a Tetris game [93] as shown in Tab. 2.4. They designed the game with varying degrees of challenges for each of the three emotional states. EEG signals combined with some peripheral physiological sensors and a questionnaire were used in the study. This is probably the first study aimed at maintaining players' engagement and flow by adapting game difficulty according to EEG assessment of players' emotion.

Players feel a sense of joy when a game balances the level of difficulty with a player's skill level. Plotnikov et al. used an open-source version of *Tetris* to in-

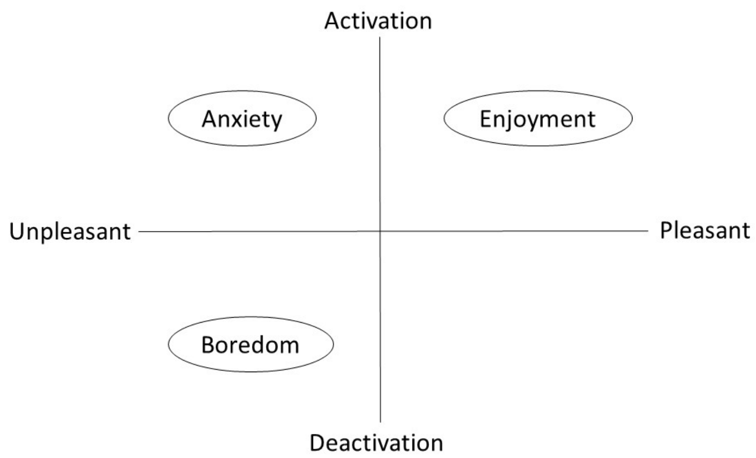


Figure 2.6: The three emotional states of flow associated with the circumplex model of affect. Adapted from [92]

vestigate players' enjoyment through EEG signal analysis [94]. The *Tetris* game in their experiment has two levels: one fast-paced and one slow-paced. The fast-paced *Tetris* level supports flow, while boredom is created by the slow-paced *Tetris* level. Questionnaires are also used to assess the flow and boredom states. After obtaining signals, analysis of variance (ANOVA) was used to compute statistical significance in the power of all frequency bands in the two conditions. Meanwhile, a Gaussian kernel SVM was used to classify the flow and boredom states of subjects. However, the work did not consider the functional decomposition of tasks in the brain.

Affective Ludology is a research area that relies on measuring affective physiological responses during player-computer interaction. EEG signals and player experience measured with questionnaires are collected [43] in relation to the impact of three game levels designed to induce boredom, immersion and flow on brain activity. This pilot study of EEG assessments of game experience identified problems like interpreting the EEG data correctly using machine learning methods and the difficulty of combining with other measures to reveal the subjective experience.

International affective picture system (IAPS) and international affective digitized sounds (IADS) are two visual and audio stimuli databases used in emotion-based

Table 2.4: Experimental scenarios, data analysis methods, associated features and brain regions in existing EEG-based emotion recognition literature

References	***Experimental Scenario***	***Data Analysis***		***Features***	***Brain Regions***
		Feature Selection	***Feature Classification***		
Chanel et al. [93]	The Tetris game	ANOVA	LDA	Alpha(T7, O1, Cz, P4, P3), beta, theta(P7, Pz, O2) and EEG_W	Occipital and parietal lobes
Nacke et al. [43]	Half life 2	ANOVA		EEG spectral power frequency bands	
Plotnikov et al. [94]	Tetris game	ANOVA	SVM	PSD	
Stikic et al. [35]	IAPS and IADS	Step wise discriminant analysis (F test)	lDFA and qDFA	PSD and wavelets of five frequency bands	Frontal, temporal and prefrontal regions
Zheng et al. [95]	Emotional movie clips		KNN, SVM, RBN,DBN	DE, PSD, DASM, RASM and DCAU in five frequency bands	
Zheng et al. [96]	Emotional movie clips		KNN, SVM, GELM, DBN, DBN HMM	DE in five freuqency bands	
Zhu et al. [86]	Emotional movie clips	MRMR	GELM	DE	Temporal lobe
Wang et al. [84]	Emotional movie clips	MRMR	KNN, multilayer perceptron and support vector machine	Six time domain features and frequency domain features	Occipital lobe, parietal lobe and temporal lobe
Becker et al. [97]	Emotional video clips	PCA and t-test	SVM	connectivity features, HOC, FD et al.	
Tiwari et al. [98]	DEAP Database	ANOVA, MRNR and RFE	SVM	Motif-based and graphic-based features	

studies [35], respectively. They are employed to elicit the corresponding emotions of subjects. Similarly, emotional movie clips also have the same function in other studies [84, 86, 96]. Also, there are two publicly accessible datasets for EEG-based emotion recognition studies, named DEAP (dataset for emotion analysis using physiological signals) [99] and SEED (SJTU emotion EEG dataset [100]. These two datasets have been used in state of art studies for exploring related EEG features and analyzing proposed data analysis algorithms [98].

Tab. 2.4 summarises the key EEG-based emotion recognition publications discussed in this section.

2.4.1.2 Data Analysis

Various kinds of machine learning methods have been used in EEG-based emotion recognition. Duan et al. first introduced differential entropy into emotion recognition [101]. As shown in Tab. 2.4, Zhu et al. used GELM to classify positive, neutral and negative emotions based on differential spectrum (DS) features. Meanwhile, minimal-redundancy-maximal-relevance (MRMR) algorithms are used to identify that the left and right temporal lobes of the gamma band, are related to emotion [86]. Later, different classification algorithms were compared and results indicated that a linear discriminant analysis (LDA), combined with ANOVA for feature selection, achieve the highest accuracy [93]. A gaussian kernel SVM was used to predict enjoyment and boredom states [94]. In recent studies, Tiwari et al. also used recursive feature elimination (RFE) to select features, together with SVM with RBF kernels to classify emotion [98].

Deep learning models have also been imported into emotion recognition recently. Zheng et al. compared deep belief networks (DBN) with KNN, SVM and GELM. The results showed that DBN, combined with a hidden markov model (HMM), had the best accuracy [96]. The advantage of DBN is that it combines feature selection and feature classification into one process, when unsupervised and supervised learning are utilised. Zheng proposed a novel group sparse canonical correlation analysis (GSCCA) method for EEG channel selection and emotion recognition [102].

The major challenge of these machine learning methods is the inter-participant and intra-participant variability of the physiological data. Several efforts have been made to address individual differences like data normalisation. Stikic et al. used two different classification methods: linear discriminant function analysis (lDFA) and quadratic discriminant function analysis (qDFA) to build user-dependent and user-independent models [35].

Liu et al. list the general unsolved issues in current algorithms for emotion recognition, as including inadequate accuracy, limited number of recognised emotions, and offline emotion recognition constraints [103]. While some researchers have looked into solving these questions, results have not yet reached a level of maturity to address these challenges properly [87, 104, 105].

2.4.1.3 Features

Researchers have analyzed evoked EEG synchronisation and desynchronisation [106] at different frequency bands during the perception of emotional stimuli [107]. The alpha band (8-12 Hz), in particular, is the most significant frequency band associated with asymmetric frontal cortical theory [108]. It is also treated as the major frequency band in emotion recognition [34, 109]. Moreover, evidence is synthesised in Knyazev's paper which shows that delta oscillation is associated with the motivational systems, theta oscillations depend on memory and emotional regulation, and alpha oscillation is involved in a variety of cognitive states such as attention and memory [110]. The same trend was reported in Bos's paper [111], which showed the use of the beta-alpha ratio as a possible indicator of the state of arousal in emotion recognition.

Nacke et al. examined the impact of boredom game conditions on EEG signals, showing that beta power (10-30 Hz) is significantly higher during states of immersion, when compared with boredom via a one-way repeated-measures analysis of variance [43]. Zheng et al.'s study has shown that beta and gamma bands reveal positive and negative emotions, meanwhile differential entropy has accurate and stable information for emotion classification [96]. ANOVA results confirmed that there are significant differences of delta and theta power between flow and immersion game levels [43].

The EEG-W feature is known to be related to cognitive processes like workload, engagement, attention and fatigue. This feature was also contained in the emotion-based feature selection process [93]. Given that EEG signals are nonlinear and non-stationary signals, recent studies employed nonlinear methods to reveal new information about human emotion states, such as higher order crossing (HOC) features, Fractal dimension (FD) features, motif-based and graphic-based features [97, 98].

2.4.1.4 Brain Regions

The prefrontal cortex gets activated during the experience of positive and negative emotions [92]. Asymmetric frontal cortical activities seem to influence the EEG study of emotional response and motivation [39, 108, 109]. Approach motivation has been observed that is related to greater left than right frontal activity, and withdrawal motivation refers to greater right rather than left frontal cortical activity [109, 112, 113]. Harmon Jones et al. suggested that the posterior cortical region may be involved in the perception of emotion as well [39].

Meanwhile, MRMR was used to identify that the left temporal lobe and right temporal lobe of the gamma band are related to emotion [86]. Research also found that the alpha band in the right occipital lobe and parietal lobe, beta band in the central site and gamma band in the left frontal lobe and right temporal lobe are associated with positive and negative emotional states [34, 35]. Meanwhile alpha power asymmetry [114] has been found in mid-frontal and anterior temporal sites and showed no subjective differences in cortical activities [109].

2.4.2 Risk-taking

In game theory and decision making, individual decision making and risk-taking behaviours are affected by personality traits and inherent motivations. Risk [54,115] is defined as the psychological state when individuals lack knowledge about the outcome of their choice. Traditionally, economic models of decision making originate from the concept of utility with regard to a rational individual choosing the best option that is likely to generate the best outcome. Motivation may act as a modifier to human perception and attitude towards risk. People with power motivation may underestimate risks or enjoy doing a high risk task or 'risk seeking'. In contrast, people with affiliation motivation may be 'risk averse' and may overestimate risks or dislike a high risk task. Achievement motivated individuals will more likely belong to the rational agent school [116].

Table 2.5: Experimental scenarios, data analysis methods, associated features and brain regions in existing neuroscience literature for risk-taking and decision-making

References	*Experimental Scenario*	*Data Analysis*	*Features*	*Brain Regions*
Schutter et al. [119]	Iowa gambling task	Correlation analysis	Alpha band	Prefrontal region
Schutter et al. [120]	Iowa gambling task	ANOVA	Theta-beta-ratio; delta-beta-retio	Prefrontal region
Masaki et al. [121]	A simple gambling task	ANOVA	SPN and MFN	
Hewig et al. [49]	Blackjack gambling task	ANOVA	ERN	ACC and nearby medial frontal areas
Gianotti et al. [47]	A seven-box task	Correlation analysis	Frequency bands	Prefrontal region
Hewig et al. [122]	Blackjack gambling task	Multiple linear regression	fMRI study	ACC
Massar et al. [48]	Gambling task	ANCOVA	Theta/beta ratio, FRN, theta and beta	ACC
Schuermann et al. [50]	Gambling task	ANOVA	FRN and P300	ACC
Studer et al. [123]	Gambling task	Correlaiton analysis and multiple linear regression	Theta band	Prefrontal region
Duan [124]	Flight situation picture	t-test	P200 and LPP	

One reason uncertainty exists in decision making is the imperfect or inadequate knowledge about the effect of the decision and the behaviour of the system. According to reinforcement learning theory (RL), the basal ganglia continuously evaluates the outcome of human behaviour or internal and external events against human expectation [49, 117, 118]. If the outcome of an event is better than expectation, phasic activity of midbrain dopaminergic neurons increases and vice versa. Neuroeconomics differentiates between two kinds of risk taking models: expectation-based models and risk-value models of risk-taking [115]. Furthermore, an individual's risk attitude varies with specific emotions and motivations.

As summarised in Tab. 2.5, in order to assess brain cortical activities for risk-taking behaviour, several gambling tasks, different features and brain regions have been investigated in existing studies. Therefore, future work should focus on the development of data analysis and feature selection methods.

2.4.2.1 Experimental Scenarios

According to classic game theory, rational people should aim to maximise their gain; however, people tend to make irrational and imperfect decisions under real life circumstances [116]. Activities in specific brain regions and personality traits are responsible for this behaviour. Mesrobian et al. used two games, the ultimatum game (UG) and the investment game (IG), to explore relevant event-related potentials (ERPs) that reflect risk-taking and imperfect decision-making [116]. In the investment game, subjects were given several points at the beginning of each trial and were asked to invest these points in a risky project, while in the other category of gambling games, participants began with nothing and attempted to gain as much money or points as possible.

A set of risk-based tasks have been used in various studies, including the cup task, lowa gambling task and balloon analogue risk task, which are summarised in Schonberg's review paper [115]. Hewig et al. used a computer Blackjack gambling task to examine the relationship [49, 122]. Schutter et al. used the Iowa gambling task to assess the influence of reward and punishment on decision-making to identify anterior symmetrical alpha activity [119]. Reward and punishment are associated with risks in these experiments. Duan presented 40 flight situation pictures, which reflects high and low-risk degree, to evoke human risk-taking attitude [124].

2.4.2.2 Data Analysis

Data analysis methods used in EEG-based risk-taking studies are simpler compared to EEG-based emotion recognition, because only several statistical tests have been used. The primary test to identify risk-related features and brain regions is ANOVA, as shown in Tab. 2.6. Moreover, correlation analysis has been used to find related EEG features and activated brain regions [47, 124]. Hewig et al. further utilised multiple linear regression to justify the function of anterior cingulate cortex (ACC) in a fMRI study [122].

2.4.2.3 Features

In terms of time domain, two event-related potentials (ERPs), the stimulus-preceding negativity (SPN) and the medial frontal negativity (MFN), have been employed to reflect affective and emotional processes of decision making in terms of risks. In Masaki's study [121], the MFN peaks at 250ms after the feedback signals increased, following larger gains. This negativity is also topographically lateralized to the right. The SPN that peaks at 1s before the feedback signals is also witnessed to rise following the larger gains. The other ERP, the error-related negativity (ERN) is also related to risk-taking and strategic decision making behaviour. The findings of Hewig et al. suggest that a higher probability of winning leads to the increase of the feedback ERN amplitude that is usually generated in the anterior cingulate cortex (ACC) and the nearby medial frontal cortical areas [49]. Moreover, three types of ERPs have been investigated and results show that the P200 is relatively higher in high risk than low risk choices. There are significant differences between positive and negative feedback in the high risk choice, instead of low risk choice with regard to feedback-related negativity (FRN); and P300 is larger in high-risk decisions [50]. In a recent study, Duan illustrated a two-stage model of risk perception and confirmed that P200 mainly focuses on early perception and detection; LPP reflects the activation and subjective evaluation of the motivation system, which belongs to risk assessment [124].

On the other hand, in terms of frequency features, Schutter et al. demonstrated using the Iowa gambling task that the frontal theta-beta-ratio and delta-beta-ratio can be regarded as indicators for motivational balance between reward and punishment systems [120]. Massar et al. provided evidence that baseline EEG theta power and theta/beta ratio are correlated with feedback-related ERP (e.g. feedback-related negativity) in a risk-taking gambling task [48]. High baseline theta power and theta/beta ratio was accompanied with decreased FRN, as well as increased risk-taking behaviour. Their study also showed that baseline theta activity and its corresponding relationship are generated in the ACC.

2.4.2.4 Brain Regions

Risk-taking behaviour causes responses in several brain regions, mainly the ACC, lateral orbitofrontal cortex and insula, which all react to monetary gains and losses [115]. The ACC is reported to influence decision-making and risk-taking behaviours; a fMRI study supports this theory. The results showed that a negative outcome of decision-making under risk is related to an activation of the dorsal ACC [122]. Additionally, activation of insular, lateral prefrontal and parietal cortices increased with rising uncertainty. Another study also reveals that posterior parietal cortex may be critical for decision-making about probability, value and expectation [125]. When subjects choose to gamble, the activation in the right anterior insula increases. When insular activation is relatively high before making a decision, subjects tend to demonstrate risk-adverse behaviour [125].

The prefrontal cortex has been demonstrated to be involved in the process of decision-making by several neuroscience studies, as shown in Tab. 2.5. Schutter et al found that relative right-sided frontal activity is associated with the riskier strategies, which contradicts the asymmetric frontal cortical activity of emotion theory [119]. As the gambling task contains the cognitive and affective process in decision-making, this result may suggest that frontal activities in the alpha band reflects the subject's inactivity. The frontal lobe is confirmed to be related to risk-taking behaviour. Floden et al. examined the association between focal frontal lobe lesion and risk-taking behaviour via their proposed gambling task [126]. Further, Gianotti et al. report that cortical activity in the right prefrontal cortex predicts individual risk-taking behaviour [47]. Individuals with high risk propensity showed higher slow-wave oscillations in the right prefrontal cortex. Studer asserted that personality and theta band power in the prefrontal cortex can predict risk taking behaviour [123]. In particular, higher theta band power in the right prefrontal cortex compared to the left is associated with increasing risk taking [123].

2.4.3 Social Factors

Considering social attitude in game theory, two types of social interactions, cooperation and competition, have been studied widely through the prisoner's dilemma, chicken game and other games [127, 128]. Combined with incentive motivation theory, power motivated individuals prefer competition as this gives them the sense of control. An affiliation motivated person, however, enjoys cooperating with others because it provides them with a feeling of belonging to a group. On the other hand, achievement motivated individuals are more likely to work alone.

Tab. 2.6 lists existing neuroscience literature about social interactions, especially cooperation and competition. These papers used games like the prisoner's dilemma, the chicken game and the ultimatum game, to examine relevant EEG features and brain regions. ANOVA and T-test were the major data analysis methods used in their studies.

2.4.3.1 Experimental Scenarios

The utimatum game (UG) has been employed to evaluate brain activities in participants evaluating the fairness of asset distribution [129, 132]. Qu et al. added a cyberball game to manipulate participants' social exclusion or inclusion, then used the ultimatum game for measuring ERP while they receive fair or unfair offers from someone previously excluded, included them or from otherwise strangers [130]. In

Table 2.6: Experimental scenarios, data analysis methods, associated features and brain regions in existing neuroscience literature for social interaction

References	*Experimental Scenario*	*Data Analysis*	*Features*	*Brain Regions*
Babiloni et al. [127]	Prisoner's dilemma	ANOVA	Alpha band	Medial prefrontal cortex and ACC
Astolfi et al. [128]	Chicken game	T test	Beta band	Orbitofrontal regions
Wu et al. [129]	The ultimatum game	ANOVA	MFN and LPP	Frontal and posterior regions
Qu et al. [130]	A cyberball game and UG	ANOVA	FRN and P300	Frontal and parietal regions, ACC
Spape et al. [131]	A turn-based computer game	ANOVA	Beta and gamma bands	Central and parietal regions
Horat et al. [132]	the UG game	ANOVA	P200 and FRN	ACC

other research, Spape et al. proposed a turn-based computer game with four cooperation and competition levels to establish the relationship between brain activity and social interactions [131].

2.4.3.2 Data Analysis

Data analysis in EEG-based social interaction studies are similar to those in EEG-based risk-taking studies. ANOVA is the prevailing approach to analyze EEG signals, which is mainly used to differentiate associated features and brain regions.

2.4.3.3 Features

According to frequency features, slowing of alpha activity is first reported among antisocial people. Mednick et al. examined a group of children to explore whether EEG alpha activity influences antisocial behaviour [133] and results support the theory. Mu rhythm (8-13 Hz) is generally reported in the sensory-motor cortex spanning the occipital and central regions, which sometimes refers to the human mirror neuron system [134]. Indeed, mu rhythm is almost in the same frequency range as alpha waves that oscillate in the occipital cortex. However, the neural activity of these two frequency bands are diverse as the alpha band is more related to attention and workload. In the central and left sites, the reduction of mu rhythm is found in both the perception and acting sessions of the rock-paper-scissors game when experiencing opponent actions [51]. This result supports the view that mu suppression is affected not only by motion, but also by the social context.

Several EEG features are also identified in the studies as shown in the Tab. 2.6 (column 4). ERPs recorded from participants showed that highly unequal offers elicited an earlier MFN (270-360 ms), and the late positive potential (LPP) in the time window of 450-650 ms was more obvious in the moderately unequal offers than highly unequal offers when compared to other player's low offers [129]. Qu et al. point out that FRN of subjects was more significant for unfair offers from people who excluded them before, and P300 was more positive for unfair offers from strangers [130]. Moreover, Horat et al. evaluated P200 and FRN as effective features for assessing social attitudes [132].

2.4.3.4 Brain Regions

Babiloni et al. utilised the prisoner's dilemma to establish that medial prefrontal cortex activity is consistent with social interaction paradigms [127]. Specifically, ACC plays a crucial role for the defect attitude [132]. Furthermore, Astolfi et al. used the chicken game to observe patterns of brain activities [128]. Their findings show that the left orbitofrontal cortex is related to this particular social interaction paradigm.

The other children-related study, conducted by Fox et al., indicated that children, who show positive social attitude and emotion, exhibited greater relative left frontal activation. In comparison, children who display social withdrawal reflect greater right frontal activation [135]. Thus resting frontal asymmetry may be an indicator for social attitude. In fact, they confirmed this assertion in their later study [136], which demonstrated the resting frontal EEG asymmetry is related to social behaviour style during preschool years. In addition, a study in adults claimed that the pattern of frontal EEG asymmetry is related to sociability instead of shyness [137].

2.5 Conclusion

In this chapter we have seen the similarities between player type models and achievement, affiliation and power motivation. We have further seen the connections between these motives and emotion, risk-taking and social attitudes, which can in turn be measured using EEG. This review justifies our decision to study achievement, affiliation and power motivation as player motive profiles in computer games, and also identifies the possibilities of using EEG technology to measure these motivations in a game context. This provides a theoretical basis for the following research challenges that this thesis seeks to address.

Chapter 3

An Abstract Mini-Game for Assessing Motivation

The work, reported in this chapter, has been partially published in the following article:

Xuejie Liu, Kathryn Merrick and Hussein Abbass (2016), *Designing artificial agents to detect the motive profile of users in virtual worlds and games.* 2016 IEEE Symposium Series on Computational Intelligence (SSCI), Athens, Greece.

3.1 Introduction

In Chapter 2 we saw that achievement, affiliation and power appear to result in different characteristics of risk-taking and social attitudes, and that these characteristics may be revealed in strategic decision-making behaviour. In this chapter, we start by presenting several conceptual models to make these hypotheses concrete in Section 3.2. We then use these conceptual models to inform the design of an abstract mini-game in Section 3.3.

A mini-game is a game fragment or short scenario that can sit within a more complex game or virtual environment. The game fragment has its own mechanics, characters, mini-plot (storyline) and environment. These are often self-contained and may be isolated from other parts of a larger game. Large games are often comprised of many mini-games connected by a more complex common storyline. A mini-game may conclude with a win or a loss for the player, or there may simply be different possible outcomes that influence the next phase of the larger game. We take this latter approach in our mini-game.

The game presented in this chapter will be used in experiments to assess the motivation of players in Chapters 5 and 6. The experimental protocol itself will be presented in Chapter 4.

3.2 Conceptual Models Linking Player Motivation and Electroencephalography

Chapter 2 traced a path from motivation theory to the brain regions associated with risk taking, social attitude and emotion. In this chapter, we begin by proposing conceptual models to associate the psychological theories of motivations—achievement, affiliation and power—to EEG measurements of these three characteristics. Section 3.2.1 examines the relationship between motivation and flow. Section 3.2.2 conceptualises motive profiles in the dimensions of risk and social attitude.

3.2.1 Flow Models

As we saw in Chapter 2, a model of flow was first proposed by Csikszentmihalyi [1], who identified eight characteristics of flow: skill-oriented challenge, concentration on the task, clear goals, explicit feedback, sense of control, transformation of time, loss of self-consciousness and the merging of action and awareness [53]. The flow model identifies a region of 'optimal experience', where games are neither boring nor anxiety inducing (see Fig. 2.1). In other words, flow occurs when people perceive challenges that perfectly match their abilities [54, 55]. If the challenge of a game is beyond a person's ability, the task begins to generate anxiety. In contrast, if games become too easy, people tend to feel bored and may quit the game quickly [56]. In the field of computer games, game designers have long recognised that different

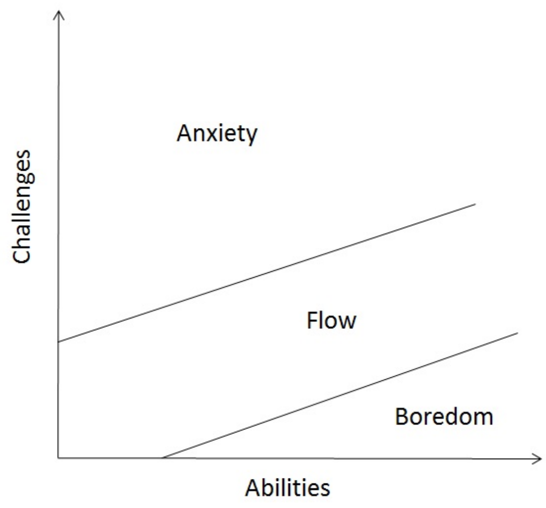


Figure 3.1: Hypothesised flow zone for an affiliation-motivated individual

players have various skills and expectations of challenges for games. To keep all players in their flow zone throughout the game, techniques such as dynamic difficulty adjustment (DDA) [2, 57] have been proposed to permit games to adapt their challenges dynamically to suit individual needs, skills or experience levels.

Earlier (Tab. 2.2, column 4) we saw the risk-related aspects of the motivations: achievement, affiliation and power. We can see that an achievement-motivated person enjoys moderately challenging tasks and is willing to take achievable risks. They tend to be rational, to calculate the risk, ensuring the success of the task. We illustrate this idea in a manner similar to the flow model as shown in Fig. 2.1.

In contrast, from the perspective of risk, individuals with dominant affiliation motivation may select goals with a higher probability of success, but lower incentive. Preference for low-risk activities can be seen as a way to avoid public competition and conflict for resources or reinforcers that are desirable to others. McClelland demonstrated this phenomenon [138] in experiments with groups of participants playing roulette. Participants placed their bets in front of a group. Their winning and loss was seen by the group. Power-motivated individuals made more high-risk bets. Meanwhile, affiliation-motivated individuals tended to make low-risk bets. Affiliation motivation is thus hypothesised to be an important balance to power

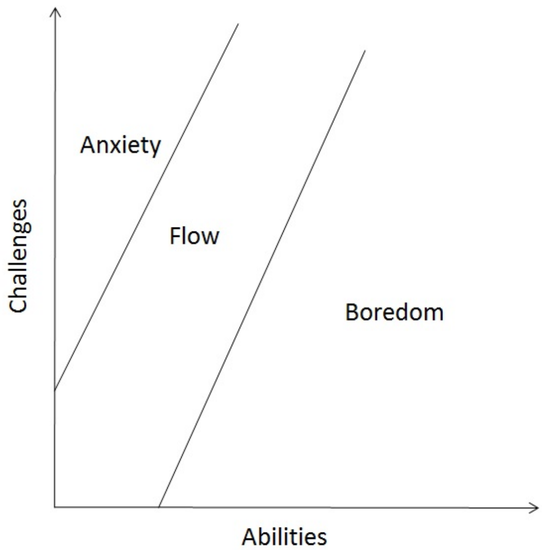


Figure 3.2: Hypothesised flow zone for a power-motivated individual

motivation [28]. We illustrate this idea in a manner similar to the flow model as shown in Fig. 3.1.

Finally, power motivated individuals select high-incentive goals, with the idea that achieving these goals will give them significant control of resources and reinforces of others. We illustrate this idea in a manner similar to the flow model as shown in Fig. 3.2. In the next section we further combine the ideas from this section in models that include the dimension of social attitude.

3.2.2 Risk-taking and Social Attitudes

While individuals may express aspects of all three motives, achievement, affiliation and power, they tend to have a dominant motive. The dominant motive has a stronger influence on decision-making than the other two, although the individual will not be conscious of this [60]. The dominant motive will result in distinct individual characteristics and emotions as summarised in Tab. 2.2. Mixed profiles of power, affiliation and achievement motivation have also been identified and associated with distinct individual characteristics. Leadership ability, for example, was found to be associated with mixed profiles of dominant power and achievement motivation.

Likewise, different levels of expression of the fear components of motivation can impact an individual's decision making. For example, individuals with strong fear of rejection become nervous and insecure in social situations when they meet people they do not know. They may fear that others may not like them and seek to bring the contact to an end. People with strong achievement-related fear of failure are often afraid of failing in situations in which their performance can be compared with that of others. Fear of failure can therefore cause an individual to act with particular thoroughness and care and to strive constantly to make no mistakes. In experiments with goal selection, strong fear of failure coupled with weak hope for success increased the range of risk-taking behaviour exhibited by participants [139]. Finally, individuals with strong fear of loss of control concentrate on avoiding the loss of influence, control or prestige. Where a choice is required, they may prefer to secure their own position rather than consider the welfare of the group.

The space of motive profiles can be conceptualised as in Fig. 3.3, which shows the three profiles with dominant hope components, and three profiles with dominant fear components, on axes of risk and social attitude [140]. The spaces between these named profiles represent the possible hybrids of these profiles. In addition, the relative dominance of each motivation varies from one individual to another. We make the conjecture that this conceptual model of the profiles will be useful for informing investigations into the use of EEG to distinguish motivation. Existing approaches used to distinguish risk and social attitude can be applied and then the results used to place an individual within the space shown in Fig. 3.3.

The challenge addressed in the remainder of this chapter is to design a game with appropriate components to permit players to express different social attitudes and risk-taking behaviour. This is the topic of the next section.

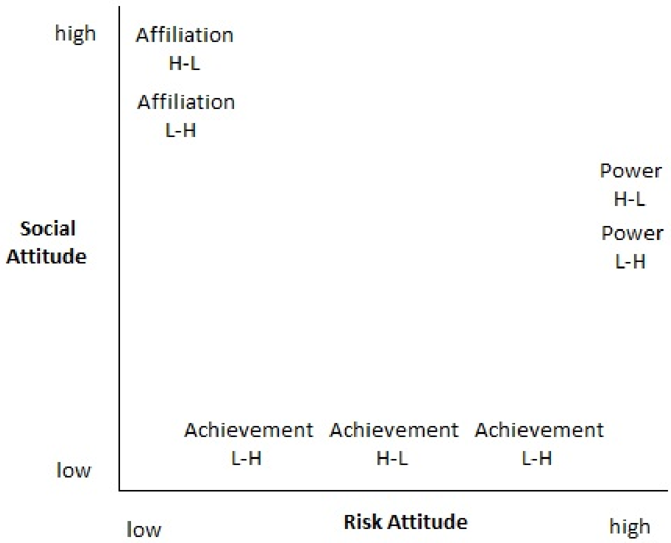


Figure 3.3: Comparison of different dominant motivations on axes of risk and social attitude. There are four possible combinations of high and low levels of hope and fear components of each motivation. High hope and low fear (H-L) or low hope and high fear (L-H) (Situations 1 or 4 respectively are indicators of motive dominance.

3.3 Game Design

This section introduces the storyline, mechanics, characters and gameplay design for our proposed mini-game. We justify each aspect of the game design with reference to the conceptual models in the previous section.

3.3.1 Storyline

We saw in the previous section that achievement, affiliation and power motivation are linked to risk-taking, social attitude and emotion. These three elemnts are ubiquitous in our everyday lives, and are thus relatively easy to frame into a mini-game. Game theory and the gambling industry offer us many examples of games that abstract real life decision-making and take into account risk and social attitude. A selection of these that have also been used in EEG studies, are summarised in Tab. 3.1. In this thesis we chose the well-known prisoners dilemma (PD) [144], which invokes both risk-taking and social interaction, as the basis for the mechanics of our

Table 3.1: Abstract games that invoke risk-taking and/or social attitude

Game	***Description***	***Invokes***
Investment Game [116]	Participants are asked to invest a certain amount of points in a risky project. The probability to win 3 times is 1/3, whereas the probability to lose the entire investment is 2/3.	Risk-taking
Iowa gambling task [119]	Participants select a card from one of four decks in each trial; two disadvantageous decks have a higher reward but also a higher possible loss, while two advantageous decks offer a lower reward but a lower possible loss.	Risk-taking
Blackjack [49]	The goal of the game is to approach 21 points as closely as possible, but to avoid getting over 21 points. Blackjack is usually played by two players competing against each other.	Risk-taking
Devil's task [47]	There are seven boxes with money in it and one of the seven boxes contains the devil that will cause players to lose their potential gains from the game. Participants decide how many boxes to open and whether to continue to earn points or take their winnings.	Risk-taking
Cambridge Gambling task [141]	A token is hidden under one of six boxes that are each one of two colours. Different trials have different ratios between box colours. On each trial, participants select a colour to bet. The colour with a higher probability (more boxes) is associated with lower potential gains, while a lower probability is related to higher potential gains.	Risk-taking
Balloon pumping task [142]	Participants pump a simulated balloon without knowing when it will explode. Each pump increases the potential reward to be gained but also the probability of explosion, which leads to loss of all potential gains in the trial.	Risk-taking
The Cups task [143]	Participants choose between a risky and safe option, which are presented through several cups. The risky option involves two to five cups with a gain or loss of \$2, \$3, or \$5, and the others contain \$0. The safe cup offers a sure gain or loss of \$1. If the risky option is selected, the payoff from one of the cups is selected at random.	Risk-taking
Gambling task [50]	There are two numbers in two squares, one containing the small number that has a higher probability of winning and a lower probability of loss, and the other has the larger number with a lower probability of winning and a higher probability of loss.	Risk-taking
Prisoner's dilemma [127]	Prisoner's dilemma derives from a situation in which two people are arrested and charged with a crime. They are held in a different room and are faced with choices between confessing or remaining silent. Their penalty depends on the choices of both players.	Risk-taking and Social attitude
Chicken game [128]	The chicken game originates from the situation that two drivers are running on the other in a one-way street. The player who swerves is called a chicken (coward). However, if neither of them stop, there will be a serious car accident. The outcome thus depends on the choices made by of both players.	Risk-taking and Social attitude

mini-game. As well as being used in EEG studies, precedents for using PD games to study motivation include work by Terhune [145] and Kuhlman et al. [146].

For the purpose of this thesis, we created a unique mini-plot, rather than using the traditional prisoner interrogation plot. This replacement of the PD plot demonstrates how our abstract scenario can represent multiple concrete scenarios. The storyline of our game revolves around the theme of 'Friends or Fortune'. In the game, players meet four virtual characters (also called non-player characters or NPCs) who approach their virtual lives with different strategies. First, players get to know the NPCs individually, by playing several rounds of a PD-like game with them. After that, they have the opportunity to team up to make friends or fortune. The player can choose which outcome (friends or fortune) they wish to pursue. The storyline is introduced to the players via an on-screen manual displayed adjacent to the interactive interface. The onscreen manual can be viewed in Appendix A of this thesis.

3.3.2 Game Mechanics

As described in the previous section, the mechanics of our mini-game are based on a PD-like game in the game domain. Each player can earn their 'fortune' or build a 'friendship' by choosing to cooperate or defect. The friendships and fortunes of each player depend on the choices of both players. The specific 'fortune' (money) payoffs V^{human} and V^{NPC} for each player and their NPC opponent in a single round of the game is shown in Fig 3.4. The money dimension is so named to represent a tangible, valuable item from day-to-day life. It is included to assist with the differentiation of achievement and power motivation. We hypothesise that power motivated individuals may prefer to maximise monetary payoff. On the other hand, we hypothesise that achievement motivated individuals will use the money reward to gauge their level of achievement in the game. Both players and NPCs accumulate the money they win in each round of the game.

Each decision also influences the 'satisfaction' S of a NPC according to [140]:

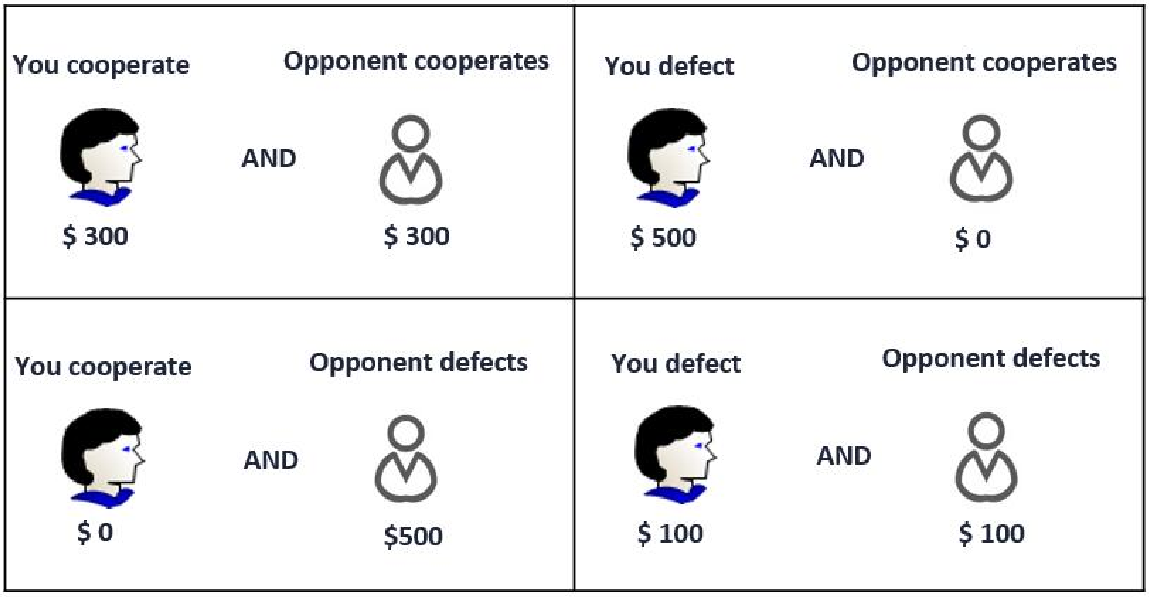


Figure 3.4: Game mechanics for accumulating 'fortune'

$$S_t = \frac{V_t^{NPC}}{V_t^{NPC} + V_t^{human}} \tag{3.1}$$

An evolving satisfaction value E_t is displayed on the game screen for each NPC. The initial value of E_t is $E_0 = 0.5$. The following update is applied to smooth the change in this value over time:

$$E_{t+1} = (1 - \lambda)S_t + \lambda E_t \tag{3.2}$$

where $\lambda = 0.5$. The satisfaction dimension is associated with social satisfaction about interactions between players and NPCs, which reflects the need for affiliation we experience in our daily life. Thus the satisfaction dimension is included to assist with the differentiation between power and affiliation motivation.

3.3.3 Non-player Characters

We have seen two themes emerging from the discussion of achievement, affiliation and power motivation. The first theme concerns social attitude: that is the number

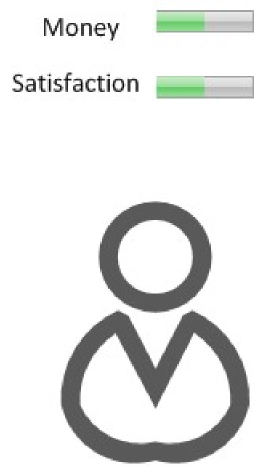


Figure 3.5: Our proposed abstract non-player characters have dimensions for money and satisfaction.

of relationships an individual may choose to initiate and maintain. The second theme concerns risk attitude: that is the degree of risk that an individual will tolerate when selecting goals.

Accordingly, we propose a model of motivation that positions achievement, affiliation and power motivation on two dimensions of risk and social attitude. We propose that power-motivated players prefer high risk tasks and have a neutral social attitude, while achievement-motivated players tend to select medium risk tasks and enjoy working alone. Affiliation-motivated players have a high social tendency and prefer low risk tasks.

In order to measure motivations during game-play, we suggest risk-taking behaviour and social attitude should be considered. Thus a range of non-player characters has been used for detecting cognitive and emotional phenomena as a basis for identifying a players motive profile.

NPC design is a multi-faceted topic, including the design of the visible avatar, as well as the design of the algorithms that control the behaviour of the avatar. A range of different approaches is taken to this latter topic. This includes rule-based, crowds and evolutionary approaches to controlling behaviour [147]. In this thesis we are interested primarily in aspects of decision making that force players to reveal their risk attitude and social attitude. We propose to do this through an examination of their behaviour. As such we do not consider the design of the visible avatar, but focus on the design of the character's cognitive attributes and decision-making behaviours.

Specifically, we propose an abstract character in Fig. 3.5 with dimensions for money and satisfaction. The money dimension is so named to represent a tangible, valuable item from day-to-day life. It is included to assist with the differentiation between achievement and power motivation. The satisfaction dimension is associated with social satisfaction regarding interactions between players and NPCs, reflecting the need for affiliation, which we experience in our daily life. Thus the satisfaction dimension is included to assist with the differentiation of power and affiliation motivation.

As described in Section 3.3.2, the money dimension is defined as the distribution of in-game money between NPCs and players using the mechanism of the prisoner's dilemma. The satisfaction dimension is proposed from a performance-approach view, as proportional to the percentage of the winnings pool accumulated by both players. Players are given the option to play with NPCs for maximising their money, maximising NPCs' satisfaction, or trading-off these objectives. This has the potential to reveal players' risk-taking and social attitudes by examining their in-game behaviour and EEG signals.

Various existing work has proposed artificial intelligence techniques of different complexity for computer controlled players of PD games [148]. We selected four classic techniques that have been hypothesised to best aid distinction between the motive profiles of their opponents [140]. These NPCs are listed as follows. It should be noted that we named the characters according to their play strategies. It also helps players to interact with these virtual characters more naturally.

- **Cooperator Candy** Candy is satisfied when she cooperates and earns the greatest share of the fortune. Candy always cooperates. Candy can thus be easily exploited if an opponent wishes to do so.

- **Defector Dan** Dan is satisfied when he defects and earns the greatest share of the fortune. Dan always defects. An opponent can satisfy Dan easily by cooperating with him. However, they will need to sacrifice their own monetary gains to do this.

- **Random Ruby** Ruby is satisfied when she earns the greatest share of the money, but has equal preference for cooperation and fortune. Ruby chooses her actions at random. As a result, playing Ruby presents a risk because, while opponents know the probabilty with which she will cooperate, they do not know precisely when she will cooperate.

- **Vengeful Vince** Vince is satisfied when he earns the greatest share of the fortune. Vince will cooperate at first, and as long as his opponent cooperates. However, if his opponent defects, he will take revenge by defecting in the next round. He always chooses the same actions his opponent chose in the previous round. This strategy is commonly known as 'Tit for Tat' (TFT).

Players are instructed that NPCs satisfaction is an indicator of how likely they are to want to make friends. The NPC strategies above are deliberately simple so that human players can learn quickly how each NPC will behave during the tutorial phase of the game. This phase will be described in detail in the next section. The responses of the human player are more likely to be deliberate rather than exploratory or curiosity motivated in the ensuing parts of the game. This is important for assessing achievement, affiliation and power motivation.

To demonstrate the differences of the four NPCs described above in terms of the way they accumulate money and satisfaction, we present a selection of charts. Each chart shows either the money or satisfaction of each NPC after 20 iterations of the PD game against theoretical human opponents with different probabilities of choosing to cooperate. These probabilities range from $P(C) = 0$ to $P(C) = 1$. The total money and satisfaction are shown in Fig. 3.6 and Fig. 3.7 respectively.

We can see from the figures that Cooperator Candy will have the highest sat-

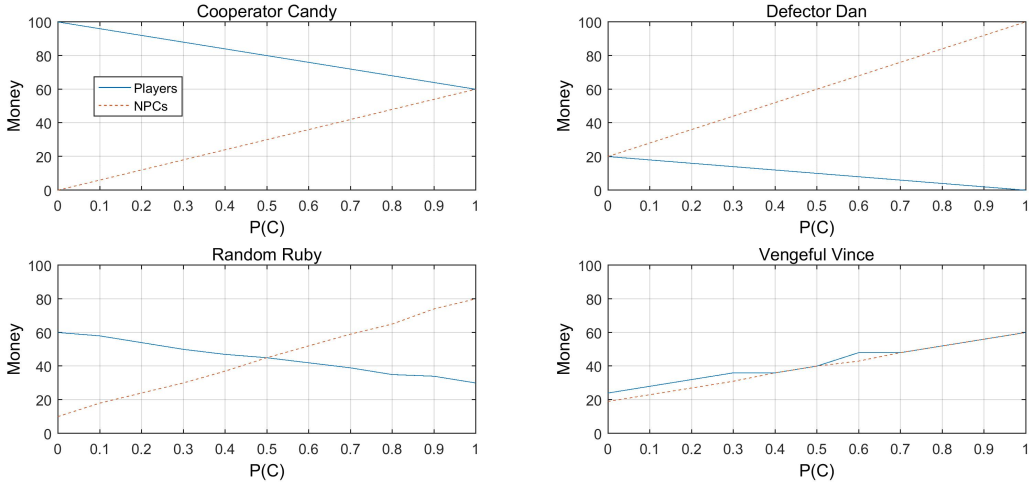


Figure 3.6: Differences in money accumulated by each non-player character playing theoretical opponents with different probabilities of choosing to cooperate. The money accumulated by the theoretical human player is also shown. (a) Cooperator Candy (b) Defector Dan (c) Random Ruby (d) Vengeful Vince

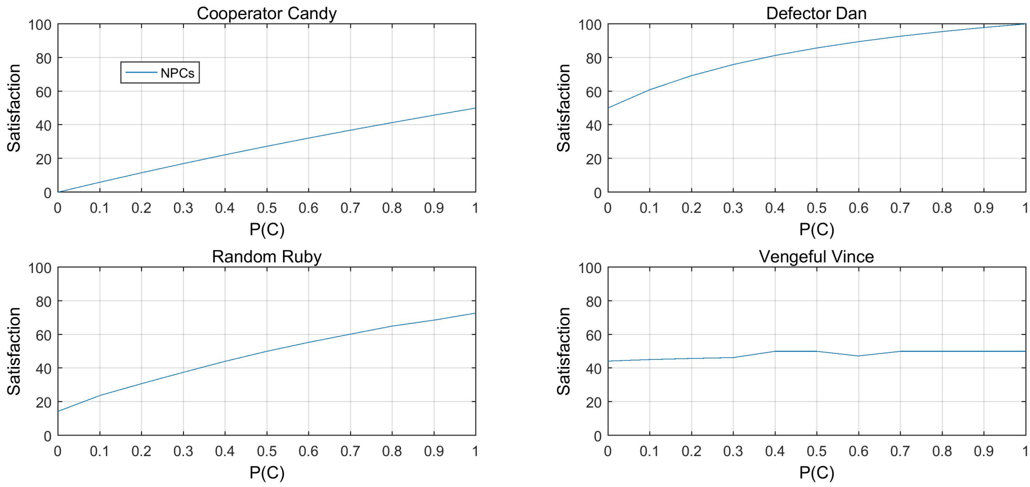


Figure 3.7: Differences in final satisfaction of each non-player character playing theoretical opponents with different probabilities of choosing to cooperate. (a) Cooperator Candy (b) Defector Dan (c) Random Ruby (d) Vengeful Vince

isfaction value against an opponent with a similar strategy. This is because both Candy and her opponent will earn a similar amount of money. Candy will have the lowest value of satisfaction against an opponent with high preference for playing defection because the opponent earns the greatest share of the money. An opponent may choose to exploit Candy to earn more money, but they will not maximise her satisfaction if they do this.

Defector Dan will have the highest money value and higher satisfaction value when he plays against an opponent that prefers cooperation, while the lowest money value if his opponent prefers defection. An opponent may choose to befriend Dan by playing cooperation, however, they will need to sacrifice their own earnings to do this.

Likewise, Random Ruby's satisfaction will be higher if her opponent chooses cooperation, but the opponent will again need to sacrifice their own earnings. Ruby will be less satisfied when opponents prefer to play defection.

Finally, Vince has generally moderate satisfaction values as a result of his adaptive strategy that permits him to perform well (in monetary terms) against opponents with a range of different preferences for choosing cooperation/defection.

3.3.4 Gameplay

Our game has several phases in which players interact in different ways with the game. These are the tutorial phase (TP), the individual play phase (IPP) and the social network phase (SNP).

3.3.4.1 Tutorial Phase

In the TP players learn about each of the four NPCs described in the previous section. First players need to follow instructions telling them how to play and how to read the user interface. Then they have an opportunity to demonstrate their understanding of various characteristics of each NPC. Once they successfully demonstrate this they can move onto the 'Individual Play' phase (IPP) of the game. A screen shot of the user interface from the tutorial phase is shown in Fig. 3.8. The TP is important to the game design because it ensures that players understand how the characters work, and that they will not be learning or experimenting during subsequent phases of the game when measurements are recorded.

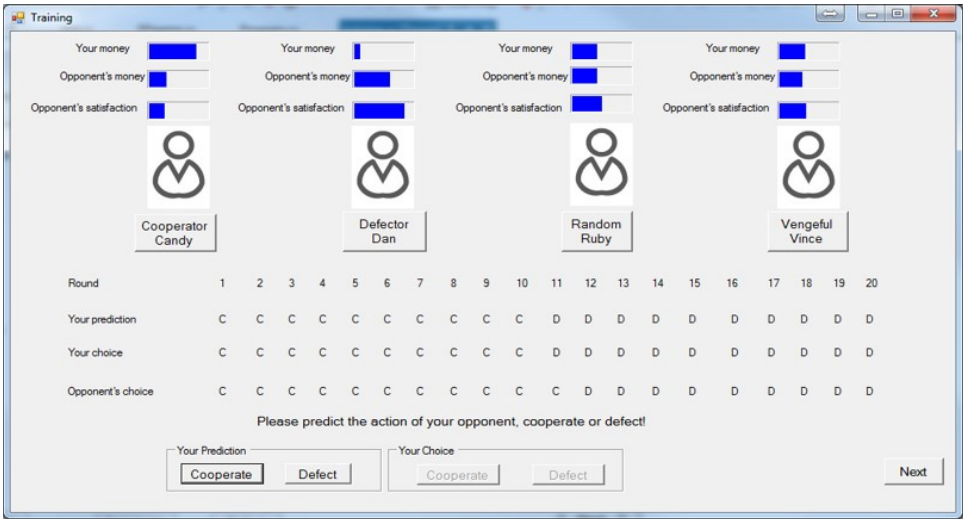


Figure 3.8: Tutorial and individual play phase user interface

3.3.4.2 Individual Play Phase

In the IPP players interact with each NPC individually. Players are instructed to play 20 rounds with each NPC in whatever way they find fun: 'for friends or fortune'. After they play with each character they do a short survey to rate their emotion on a three point scale (positive, neutral or negative). The user interface for the IPP is shown in Fig. 3.8, with an additional screen to collect player emotion information. The IPP is important to the game design as it gathers behaviour data necessary for understanding achievement motivation in a minimal social setting (one-vs-one play). The responses of NPCs in the IPP were described in the previous section.

3.3.4.3 Social Network Phase

In the SNP, players first build a social network comprising their selection of up to eight instances of the four NPCs they met in the previous phases of the game. They then play 20 rounds of the game with their network. Players score points in a pairwise fashion (that is, this part of the game is not an n-player PD). The user interface for the SNP is shown in Fig 3.9. In the SNP, all NPCs satisfaction is further amplified by the size of the social network they belong to. This is implemented as follows: A factor $r = N/8$ is incorporated into the equation to represent the influence

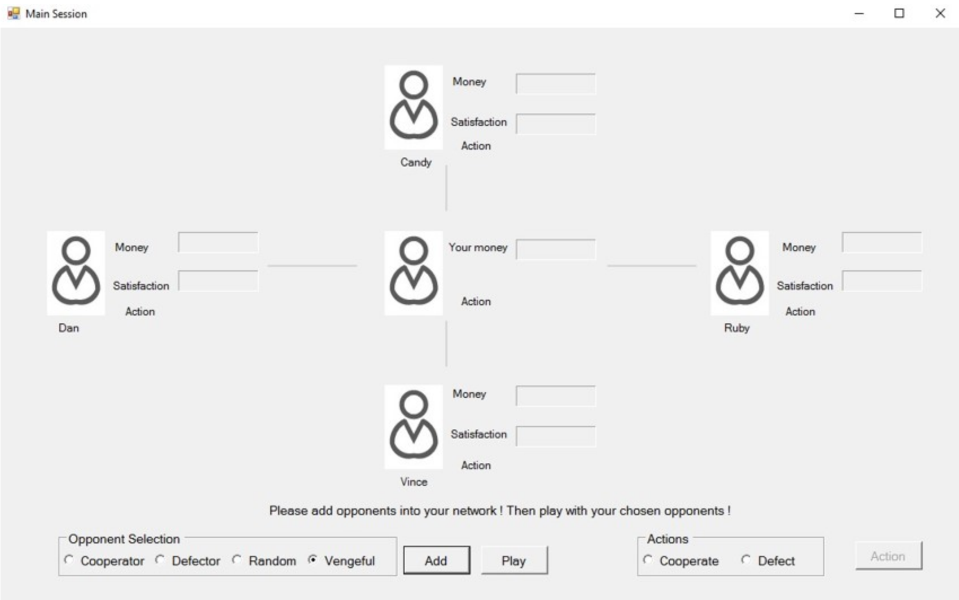


Figure 3.9: Social network phase user interface

of network size on network satisfaction. N is the number of selected opponents in the network.

$$E_t^{NPC} = S_t^{NPC}(1 + r) \tag{3.3}$$

E_t^{NPC} is the satisfaction value displayed on the game interface for each NPC. S_t^{NPC} is the satisfaction value calculated by the definition. The network satisfaction is also updated using Eqn. 3.2 to smooth the changes of the value throughout the game.

3.4 Discussion

The proposed abstract mini-game has characteristics that make it potentially suitable for use within a commercial game. For example, it has the potential for application in massively multiplayer online role-playing games (MMORPGs). In such games, players control avatars to interact with NPCs. Following a storyline and game mechanics, players can control and interact with game elements, and receive feedback regularly. The scenario in which players interact with our specially designed NPCs could be appropriately isolated in a larger game through terrain conditions or levelling constraints.

However, currently, our mini-game is designed to be simple, in order to control the variables that may influence player motive profiling. Commercial games generally have clear goals, like winning money/points, however, the goal of our proposed game is defined by players. They choose how to play the game for earning money, building friendships and trade-offs between these. Moreover, the environment or interface is designed simply without any visual aesthetic, which is also controlled compared to standard games. Further, the dynamics of the mini-game are controlled with a limited level of unpredictable elements (e.g. random NPC).

3.5 Conclusion

This chapter has presented and justified the design of a mini-game that can be used to assess motivation. The next chapter describes the experimental protocol that uses this game to assess motivation. Results will be presented in Chapters 5, 6 and 7.

Chapter 4

Experimental Protocol and Participant Demographics

The work, reported in this chapter, has been partially published in the following article:

Xuejie Liu, Kathryn Kasmarik and Hussein Abbass (2018), *Assessing Player Profiles of Achievement, Affiliation and Power Motivation using Electroencephalography* (under review).

4.1 Introduction

In the previous chapter we proposed an abstract mini-game called *'Friends or Fortune'*, which has the potential to reveal human motivation through their risk-taking and social behaviour in the game. This chapter describes an experimental protocol incorporating the game to collect behavioural data and electroencephalography data from the game, and motivation data from a multi-motive grid test. The experimental protocol is described in Section 4.1, including the data we collect and the procedures we use. Section 4.2 presents demographic data from the subjects who particpated in the experiments. Further analysis showing how the game can be used to assess motivation is presented in Chapters 5, 6 and 7.

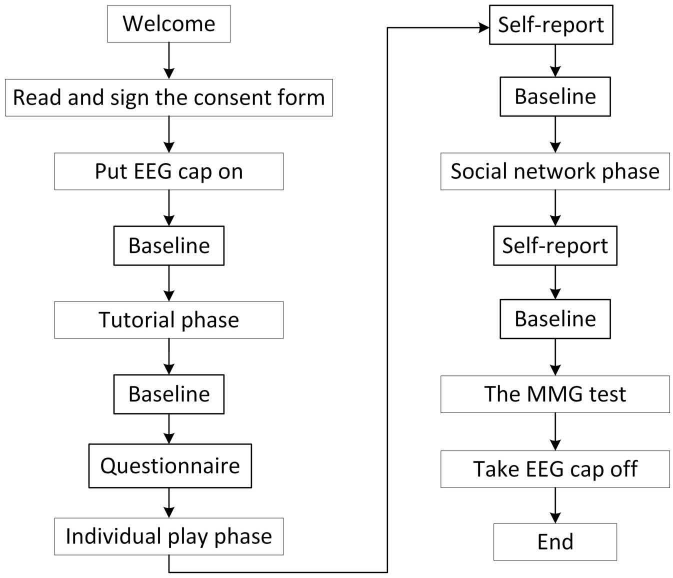


Figure 4.1: Procedure of the experiment

4.2 Experimental Protocol

The experiment was executed following the procedure shown in Fig. 4.1. The experimental design method is a within-participant design, with all participants following the same procedure. The experiment was conducted under the UNSW Canberra Ethics Approval protocol HC17430. Subjects were recruited on a voluntary basis.

The experiment was performed in a laboratory, located at the UNSW Canberra campus. Subjects sat comfortably in a chair in front of two screens, as shown in Fig. 4.2. The main screen showed the game interface that subjects can interact with. The second screen showed the game manual with the instructions that subjects follow to play the game (see Appendix A). The following subsections describe the experimental procedures that are interleaved with the game play.

4.2.1 Welcome

First, subjects were welcomed and asked to read the consent form carefully and sign it prior to the experiment. Participants were also informed of their right to

Figure 4.2: Experimental setup and environment

withdraw their data at any phase of their participation without negative consequences.

4.2.2 Electroencephalography Setup

Next, the experimenter prepared the EEG cap with dry pad and flex sensors, using seven dry pad sensors on the front-most band of the cap and 67 flex sensors on the other bands. Sometimes the flex sensors were used in the front-most band because of dense hair there for particular subjects. Then the experimenter put the cap on the subject's head, making sure to tighten the band enough to obtain good contact, but avoiding over-tightening the chin strap to prevent discomfort.

For recording the EEG signals, our experiment employed the HD 72 EEG cap from Cognionics Company [149]. HD 72 is a high density mobile dry EEG platform that supports up to 64 channels. As a dry EEG system, it does not require gel to buffer against contact loss of sensor movements relative to the scalp. It is designed for use with both dry pad sensors (on bare scalp) and flex sensors (through hair). The HD 72 follows the higher-resolution international 10-10 electrodes placement system with 64 channels signals [150].

To use the HD 72 to record the EEG signal, the Cognionics data acquisition software must be installed in the computer. The software provides a real-time display of raw signals and live electrode impedance check that helps the experimenter to check the EEG signal quality. The software interface was shown in an ipad screen for real-time signal monitoring. The signals were recorded at the sampling rate of 250Hz.

To label the EEG signals, the Cognionics Wireless Trigger enables the transmission of precision time markers to our wireless EEG headsets. The wireless Trigger supports a USB virtual serial port interface for modern computers that lack legacy serial and parallel ports. The port settings were 57600, 8-N-1, no flow control, and the driver's latency timer was set to 1ms.

With the EEG cap on, subjects firstly completed a baseline task that required them to sit for 2 minutes with their eyes closed, then relaxing, followed by 2 minutes with their eyes open, and then relaxing.

4.2.3 Introduction and Tutorial Phase

Following the EEG setup and initial baseline task, participants start to play the game described in Chapter 2, following the instructions displayed in the on-screen manual (see Appendix A). The game manual contains four sections with an introduction, the tutorial phase (TP), the individual play phase (IPP) and the social network phase (SNP). In the introduction section of the manual, players are introduced to the game storyline, and the play strategies of the four non-player characters (NPCs). They were also informed that the aim of the game is to earn their 'fortune' or build 'friendships' by choosing to cooperate or defect with the NPCs. They were then prompted to start the TP.

In the TP, players learned about each of the four NPCs described in Chapter 2. First players needed to follow instructions telling them how to play and how to read

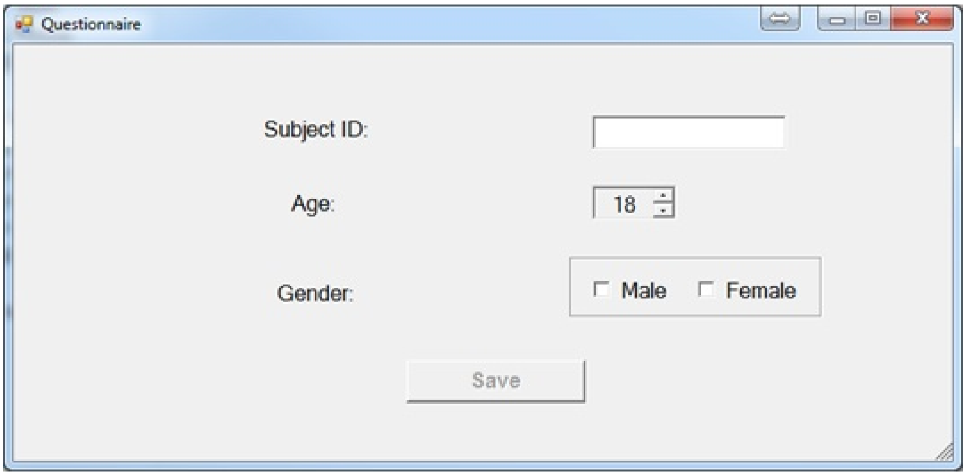


Figure 4.3: Form to collect demographic data

the user interface. Then they had an opportunity to demonstrate their understanding of various characteristics of each NPC. Once they successfully demonstrated this they can move onto the IPP as detailed in Chapter 2 (and summarised in Fig. 4.1).

Before the IPP commences, participants were given a short survey to collect their age and gender. The data collection form is shown in Fig. 4.3. A summary of this demographic data is presented in Section 4.3.1. They also performed the EEG baseline task, described in the previous section, for a second time.

4.2.4 Individual Play Phase

After the TP, participants went on to play the IPP as described in Chapter 2. While they played, we collected the following behavioural data for each participant:

- number of times players needed to repeat the TP
- players' predictions about how their opponents would play in each IPP round
- players' actions (cooperate or defect) in each IPP round
- response time to click the cooperate or defect button
- players' accumulated money after playing each NPC in the IPP (M^P)

- players' self-reported emotion after playing each NPC individually for 20 rounds (E^P)

- NPCs' accumulated money after 20 IPP rounds (M^C, M^D, M^R , M^V)

- NPCs' accumulated satisfaction after 20 IPP rounds (E^C, E^D, E^R , E^V)

- total play time against each NPC(T^C, T^D, T^R , T^V)

We further computed the following values:

- probability of cooperating with Candy in the IPP (P^C)

- probability of cooperating with Dan in the IPP (P^D)

- probability of cooperating with Ruby in the IPP (P^R)

- probability of cooperating with Vince in the IPP (P^V)

- average response time with Candy in the IPP (R^C)

- average response time with Dan in the IPP (R^D)

- average response time with Ruby in the IPP (R^R)

- average response time with Vince in the IPP (R^V)

- average response time with network in the IPP (R^N)

For the purpose of EEG data collection, we designed an event coding system to record in-game events with the frequency and accuracy of the EEG recording system. This event coding system sends event byte codes through the Cognionics event trigger to the EEG signal acquisition hardware and software. Tab. 4.1 displays our in-game event coding system for the tutorial and individual play phases. We grouped the in-game event into two items: human actions and machine actions.

Also for the purpose of EEG data collection, we implemented a delay of 500ms between the events. For instance, when subjects clicked the cooperate button, they

Table 4.1: In-game event coding system for TP and IPP

Items		***Description***	***Code***
Human Actions	***NPC***	Cooperator Candy	1
		Defector Dan	2
		Random Ruby	3
		Revenger Robin	4
	Predictions	Cooperate	5
		Defect	6
	Choices	Cooperate	7
		Defect	8
Machine Actions	***Money***	Increase	9
		No change	10
		Decrease	11
	Satisfaction	Increase	12
		No change	13
		Decrease	14

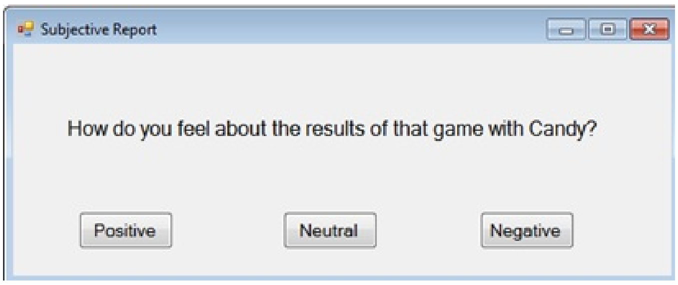


Figure 4.4: Example of a form to collect self-reported emotions

received the money feedback after 500ms and satisfaction feedback after another 500ms. This helps us to analyse the EEG signals more precisely.

After the IPP, participants performed the EEG baseline task for a third time.

4.2.5 Self-Reported Emotion

During the IPP, participants were asked to report on their emotion (either positive, negative or neutral) after they played with each NPC. This is collected using an on-screen form as shown in Fig. 4.4.

4.2.6 Social Network Phase

Following the IPP, subjects completed the SNP as described in Chapter 2. The following data was collected:

- number of Cooperator Candy NPCs in the network (N^C)
- number of Defector Dan NPCs in the network (N^D)
- number of Random Ruby NPCs in the network (N^R)
- number of Vengeful Vince NPCs in the network (N^V)
- the sequence of choosing NPCs in the network
- players' actions (cooperate or defect) in each SNP round
- response time for each action
- players' accumulated money against their social network
- players' emotion during playing with their social network
- NPCs' accumulated money during the SNP
- each NPC's accumulated satisfaction during the SNP
- total play time against social network (T^N)

As in the IPP, an event coding scheme was used to collect EEG events during the SNP. This coding scheme is shown in Tab. 4.2.

After the SNP, participants performed the EEG baseline task for a fourth and final time.

Table 4.2: In-game event coding system for SNP

Items		***Description***	***Code***
Human Actions		Play	15
	Add opponent	Cooperator Candy	16
		Defector Dan	17
		Random Ruby	18
		Revenger Robin	19
	Actions	Cooperate	20
		Defect	21
Machine Actions	***Money***	Increase	22
		No change	23
		Decrease	24
	Satisfaction	Increase	25
		No change	26
		Decrease	27

4.2.7 Multi-motive Grid Test

Finally, subjects were required to take the multi-motive grid (MMG) test to assess their motivations. The MMG test was performed at end of the experiment, because subjects should not be aware of the purpose of the experiment. The MMG test includes pictures and statements to measure three motives, and subjects get a result report after taking the test. If subjects conjecture from the MMG test that they will be identified as achievement, affiliation and power motived, their gameplay behaviour and EEG signals might be affected, which would bias the experimental results.

The details of this commercially available test were discussed in Chapter 2. At the end of this phase we collected the following data:

- hope for success (HE)
- fear of failure (FM)
- hope for control (HK)
- fear of loss of control (FK)
- hope for social acceptance (FA)
- fear of rejection (FZ)

4.3 Subject Demographics and Statistical Data

4.3.1 Age and Gender

Twenty-three subjects (11 males and 12 females) from local universities took part in this experiment, aged from 24 to 46 years old (M=29, SD=4.99).

4.3.2 Multi-Motive Grid Statistics

As detailed in Chapter 2, the MMG test provides scores for six variables: hope for success (achievement), fear of failure (achievement), hope for control (power), fear of loss of control (power), hope for affiliation (affiliation) and fear of rejection (affiliation). Raw values are produced for all scales. The output consists of a results table, which gives raw and standard scores for all scales [30]. Fig. 4.5, Fig. 4.6 and Fig. 4.7 show the distribution of raw scores from the MMG. These charts show that we have individuals with a variety of motive profiles in our sample. But it should be noted that there are very few individuals with both low fear of failure and low hope for success, as shown by the gap in the bottom left corner of Fig. 4.5. Likewise, there is also a gap in the top left corner of Fig. 4.6 that indicates there were very few individuals with high fear of loss of control and low hope for control.

4.3.3 Behavioural Statistics

This section presents a number of visualisations of the way subjects interacted with the different NPCs in the IPP and SNP. Fig. 4.8, Fig. 4.9, Fig. 4.10 and Fig. 4.11 show the distributions of probabilities that subjects will choose cooperate against each NPC. We can see in each figure that there is one larger bin, but also one or more smaller bins. This indicates that while many subjects played the same way against each NPC, there were differences in play strategies chosen. Chapters 5, 6 and 7 will investigate the relationships between these different strategies and differences in MMG and EEG data.

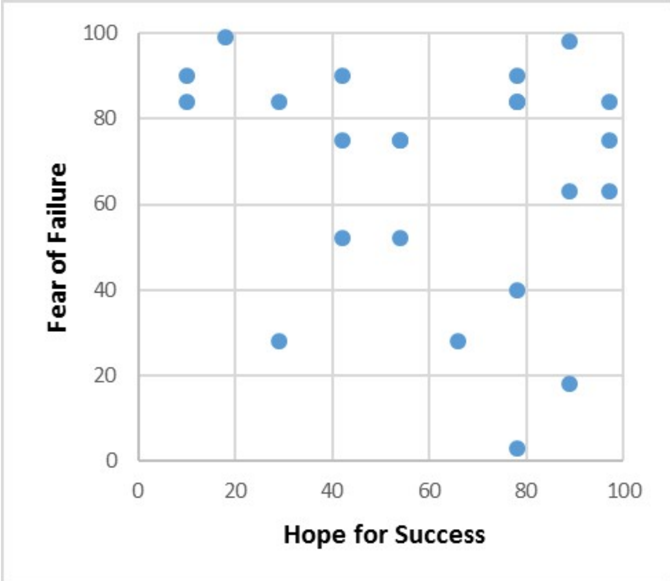


Figure 4.5: Visualisation of raw MMG data: Subjects' hope versus fear components for achievement motivation

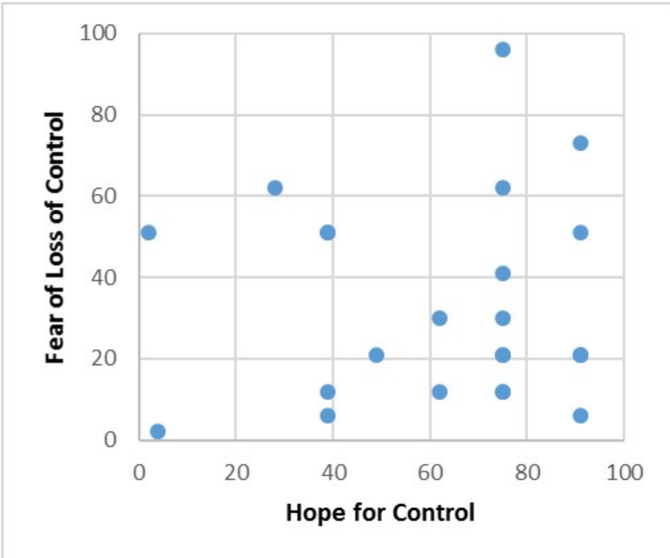


Figure 4.6: Visualisation of raw MMG data: Subjects' hope versus fear components for power motivation

Fig. 4.12 shows the number of each type of NPC which subjects chose to add to their network in the SNP. Again we see that there is variation between subjects in the total number of NPCs they chose to add to their networks, and also in which NPCs they added to their network. Chapters 5-7 also investigate the relationships between these variables and MMG data.

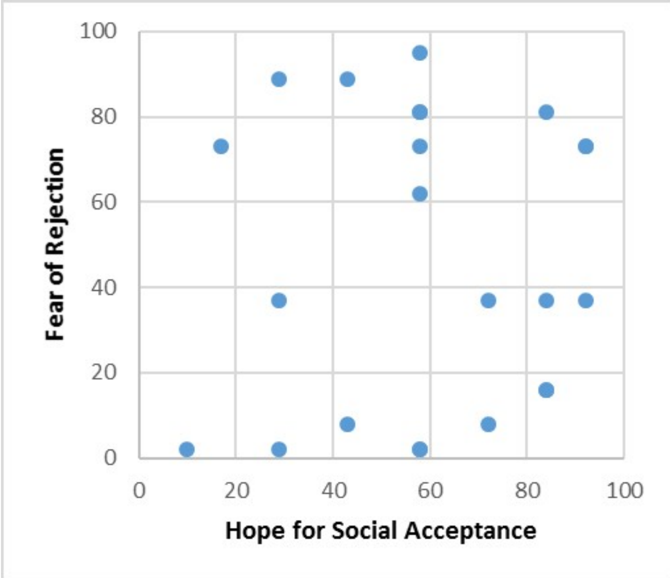


Figure 4.7: Visualisation of raw MMG data: Subjects' hope versus fear components for affiliation motivation

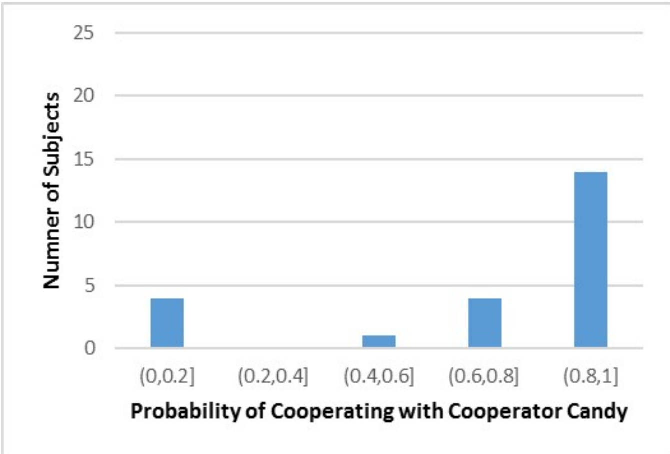


Figure 4.8: Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Candy

4.3.4 EEG Signal Sample

As for EEG signal processing, one round can be considered as a trial that has three labels: action, money and satisfaction. We present one example in Fig. 4.13 for illustrative purposes. Each trial has 2.5s, including a first 0.5s baseline (from -0.5s to 0s), that comes before a player's action, which is labelled as t=0s in the trial. After that, we also labelled the onset of money feedback and the onset of satisfaction

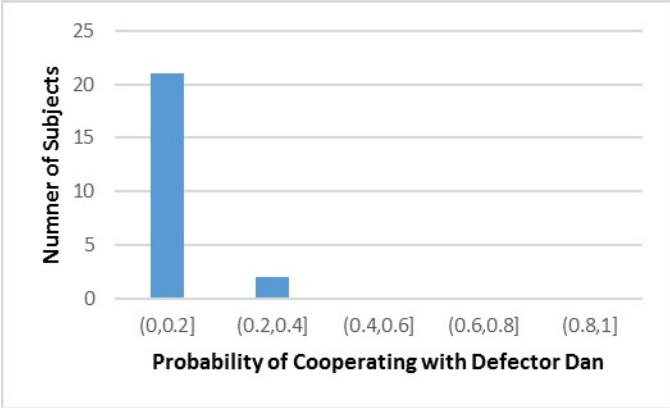


Figure 4.9: Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Dan

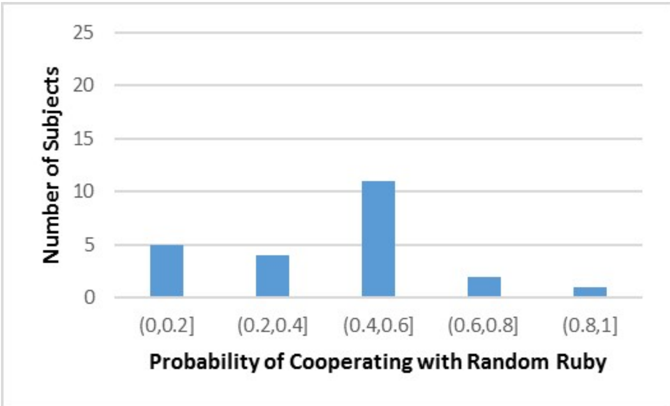


Figure 4.10: Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Ruby

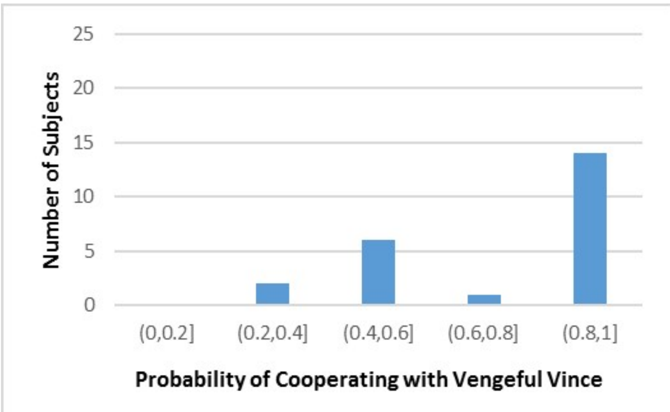


Figure 4.11: Visualisation of raw behavioural data: Subjects' probability of choosing cooperation against Vince

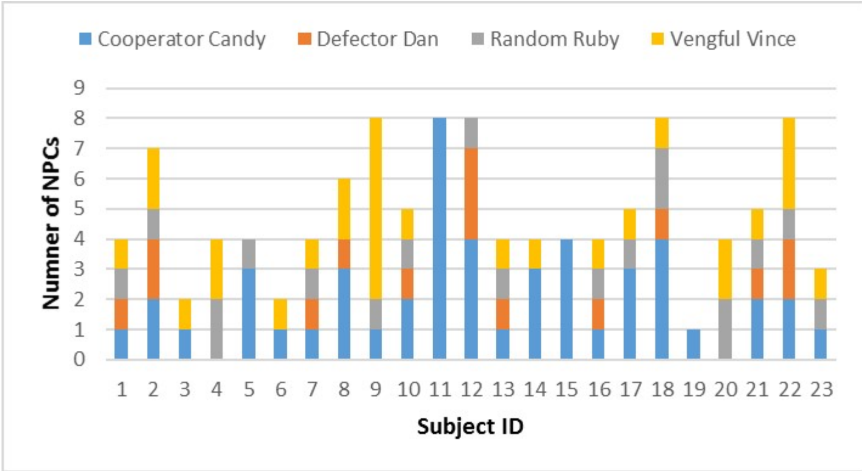


Figure 4.12: Visualisation of raw behavioural data: The number of each type of NPC which subjects chose to add to their network in SNP

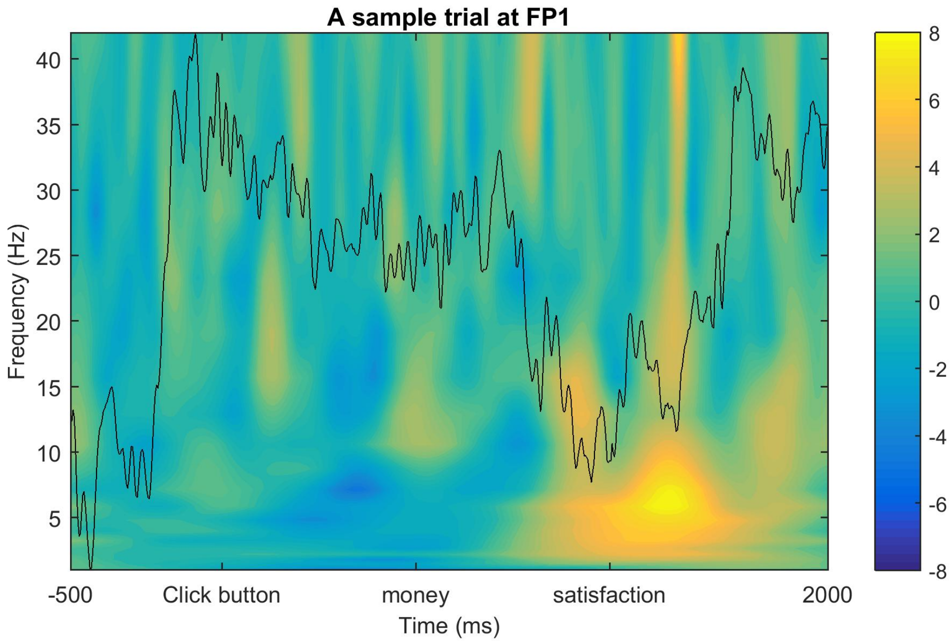


Figure 4.13: Visualisation of raw EEG data in a particular trial. Each trial consists of 0.5s baseline, than comes the actions, follows by money and satisfaction feedback.

feedback. There are 20 trials (the same as player behaviour in 20 rounds) for each NPC in the IPP, and also 20 trials (the same as player behaviour in 20 rounds) for social network in the SNP.

4.4 Conclusion

This chapter has presented an experimental protocol that uses the mini-game in Chapter 2. We presented a selection of demographic and statistical data from subjects who participated in the experiment, showing that there are variations in both their motive profiles (accoding to the MMG) and their game play behaviour. Chapters 5-7 will analyse this data in more detail to identify the relationships between player behaviour, motivation and EEG data.

Chapter 5

Classifying Motivation From Player Behaviour and Electroencephalographic Data

The work, reported in this chapter, has been partially published in the following article:

Xuejie Liu, Kathryn Kasmarik and Hussein Abbass (2018), *Assessing Player Profiles of Achievement, Affiliation and Power Motivation using Electroencephalography* (under review).

5.1 Introduction

In Chapter 3, we proposed an abstract mini-game that we hypothesised can permit us to profile human motivation. In Chapter 4 we described a human experiment using our proposed game. Three kinds of data were collected in this experiment: player behaviour data, electroencephalographic data and psychological data using a multi-motive grid test. In this chapter, we regard the psychological test data as the ground-truth, which permitted us to label experimental subjects with different labelling schemes for achievement, affiliation and power motivation. We then used this labelled data to train classifiers to assess motivation from both player behaviour and electroencephalographic data. We compared the performance of different classifiers, different labelling schemes and different input data. These results are reported in the remainder of this chapter, with supporting experiments in Appendix B and Appendix C.

This chapter is structured as follows. Section 5.2 explains how we labelled our data, and the results of motivation classification from player behaviour. Section 5.3 presents the methodology and findings for motivation classification from EEG data. It also compares these EEG results with player behaviour results.

5.2 Classifying Player Motivation from Player Behaviour

5.2.1 Aim

The aim of this experiment is to determine whether we can train a classifier to assess an individual's motive profile from their behaviour in our abstract mini-game. In order to answer this question, we first need to define what we mean by 'assess' via identifying an appropriate subject labelling scheme. Three subject labelling schemes based on the MMG test output are proposed and compared based on classification performance.

5.2.2 Hypothesis

We hypothesise that it will be possible to predict players' subjective motivation strength in three bands (average, below average and above average) and their situation (H-L, L-H, H-H and L-L) from player behaviour data.

5.2.3 Method

This section discusses the methods for subject labelling, input data for classification and types of classifiers used in this experiment.

5.2.3.1 Input data and Labelling Scheme

We selected a subset of behaviour data for this classification. The input data for the classifier was as follows for the IPP:

- probability of cooperating with Candy in the IPP (P^C)
- probability of cooperating with Dan in the IPP (P^D)
- probability of cooperating with Ruby in the IPP (P^R)
- probability of cooperating with Vince in the IPP (P^V)

For classification from the SNP the input data was:

- percentage of Cooperator Candy NPCs in the network (N^C)
- percentage of Defector Dan NPCs in the network (N^D)
- percentage of Random Ruby NPCs in the network (N^R)
- percentage of Vengeful Vince NPCs in the network (N^V)

We limited this experiment to this subset of input, because in subsequent experiments classifying motivation from EEG data it was possible to collect the EEG data from just after the button click when a player made the choice to cooperate or defect, and just after the result of their action was displayed on the screen. Thus we processed the EEG signals that were relevant to each behaviour. These input properties were a logical starting point.

We experimented with three labelling schemes for assessing motivation. As we saw in Chapter 2, the MMG test provides scores for six variables: hope for success, fear of failure, hope for control, fear of loss of control, hope for affiliation and fear of rejection.

Table 5.1: Subject labelling scheme 1 (LS1). There are three levels (above average, average and below average) of six motivation variables: hope for success (achievement, HE), fear of failure (achievement, FM), hope for control (power, HK), fear of loss of control (power, FK), hope for affiliation (affiliation, HA) and fear of rejection (affiliation, FZ).

Subject ID	***HE***	***FM***	***HK***	***FK***	***HA***	***FZ***
1	above	average	above	average	above	average
2	above	above	average	above	average	average
3	average	average	average	below	average	average
4	below	above	average	average	average	average
5	average	above	average	average	average	above
6	average	above	average	below	average	average
7	average	average	average	below	below	below
8	average	above	average	average	average	above
9	above	average	average	average	average	below
10	average	above	average	average	above	average
11	average	average	average	below	above	average
12	below	above	average	average	above	below
13	average	average	average	average	above	below
14	above	below	below	below	average	below
15	average	above	average	average	average	above
16	above	above	above	average	above	average
17	average	above	above	average	average	average
18	average	average	above	average	average	average
19	average	average	average	average	average	below
20	average	average	average	below	average	below
21	above	average	above	below	above	average
22	above	average	average	average	average	average
23	average	average	below	average	average	below

Table 5.2: Subject labelling scheme 2 (LS2). There are four situations (H-L, L-H, H-H and L-L) of three motivations (achievement, affiliation and power).

Subject ID	***achievement***	***power***	***affiation***
1	H-L	H-L	H-L
2	H-H	H-H	L-L
3	H-H	H-L	H-L
4	L-H	H-L	H-H
5	L-H	H-H	L-H
6	H-H	L-L	H-H
7	L-H	L-L	L-L
8	H-H	H-L	H-H
9	H-H	L-H	L-L
10	L-H	L-H	H-H
11	L-H	H-L	H-L
12	L-H	H-L	H-L
13	H-H	H-L	H-L
14	H-L	L-L	H-L
15	L-H	L-L	L-H
16	H-H	H-L	H-H
17	H-H	H-H	H-H
18	H-L	H-H	H-H
19	H-H	H-L	H-L
20	L-L	H-L	L-L
21	H-H	H-L	H-H
22	H-H	L-H	L-H
23	H-L	L-H	H-L

The first labelling scheme (LS1) uses the interpretation of the multi-motive grid (MMG) shown in Fig. 2.4. Participants were labelled with one of three strength-related labels (average, above average or below average) for each of the six variables. Six classifiers were then trained to recognise the strength of a person's hope and fear components for each motive. Tab. 5.1 presents the labelling of our 23 subjects according to the first labelling scheme.

The second labelling scheme (LS2) drew on the situation based interpretation of motivation from Fig. 2.5. For each motive, four scenarios can emerge from the scored results. These represent four possible combinations of high and low levels of hope and fear: high hope and low fear (H-L), low hope and high fear (L-H), low hope and fear (L-L) or high hope and fear (H-H). In LS2, participants were labelled with one of these four situation labels (H-L, L-H, H-H, L-L) for each of the three motives, achievement, affiliation and power. We categorised subjects' MMG scores as 'high' if they were greater than 50, otherwise as 'low'. The second labelling of

Table 5.3: Subject labelling scheme 3 (LS3). There are three levels (H-L, L-H and other) of three motivations (achievement, affiliation and power).

Subject ID	***achievement***	***affiation***	***power***
1	H-L	H-L	H-L
2	Other	Other	Other
3	Other	H-L	H-L
4	L-H	Other	H-L
5	L-H	L-H	Other
6	Other	Other	Other
7	L-H	Other	Other
8	Other	Other	H-L
9	Other	Other	L-H
10	L-H	Other	L-H
11	L-H	H-L	H-L
12	L-H	H-L	H-L
13	Other	H-L	H-L
14	H-L	H-L	Other
15	L-H	L-H	Other
16	Other	Other	H-L
17	Other	Other	Other
18	H-L	Other	Other
19	Other	H-L	H-L
20	Other	Other	H-L
21	Other	Other	H-L
22	Other	L-H	L-H
23	H-L	H-L	L-H

our 23 subjects is shown in Tab. 5.2.

Finally, for the third labelling scheme (LS3), we use the fact that H-L and L-H in particular are indicators of motive dominance. In contrast, high hope and high fear (H-H) and low hope and low fear (L-L) are situations where there is a high conflict between hope and fear and no dominance. Thus it is possible to combine these two into a single class named 'other'. In LS3, participants were labelled with one of three labels for each of the three motives (H-L, L-H, other). The labelling of our 23 subjects according to this scheme is listed in Tab. 5.3.

5.2.3.2 Classification

A number of different classifiers were considered for this research (see Appendix B). The results discussed in this chapter use K-Nearest Neighbour (KNN) classification [151]. KNN is a supervised machine-learning algorithm. When predicting a new sample, KNN finds the K most similar training samples (the nearest neighbours) and their corresponding labels. Then it takes a majority vote from the K nearest neighbours and sets the winning label as the class for the new sample. We chose KNN because it is a completely non-parametric approach that works well in situations where the decision boundary is highly non-linear. It is a computationally intensive method, but works well with small data sets. We selected the value of K as 3 or 6 for different conditions based on the classification performance. Euclidean distance was used as the similarity function. Five fold cross-validation was chosen. This split the whole dataset into five folds, each of which was used for training and testing. The mean accuracy and standard deviation were estimated over 10 runs of five fold cross-validation.

We also calculated the kappa statistic for each classification. The kappa statistic is a measure of how closely the instances classified by the machine learning classifier, rather than controlled by a random classifier. The kappa statistic not only shed light into how the classifier itself performed, but the kappa statistic for one model is directly comparable to the kappa statistic for any other model used for the same classification task. In general, the number of kappa statistic less than 0.2 can be considered as slight, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1 as almost perfect. Kappa statistics can be negative when the observed accuracy is less than the expected accuracy, which means that there is less agreement than would be expected by chance given the marginal distributions of ratings.

5.2.4 Results and Discussion

First, we trained a classifier to assess an individual's motive profiles from their behaviour in the abstract mini-game. Results from the IPP and SNP across the three subject labelling schemes are presented in Tab. 5.4. In the IPP, we first compared the hope and fear components in LS1. It can be observed from the table that using LS1 hope components have 23%, 15% and 25% higher accuracies than fear components for achievement, affiliation and power motivation. An independent t-test was used to assess the statistical significance of the differences between the hope and fear component to have p-value less than 0.001 for achievement ($t(23) = 6.05, P < 0.001$), affiliation ($t(23) = 4.11, P < 0.001$) and power ($t(23) = 6.93, P < 0.001$).

Further comparison of LS1 with LS3, for achievement motivation showed that LS1 hope component had 14% higher accuracy, and that fear component had 9% less accuracy than LS3. Results of a t-test indicated that the difference using the case of the hope component was strongly statistically significant ($t(23) = 3.60, P < 0.001$). The difference for the fear component was also statistically significant ($t(23) = -2.37, P < 0.05$). As for affiliation motivation, LS3 had 9% and 24% improvement of accuracy compared to LS1. A t-test showed that the difference between LS1 hope component and LS3 was statistically significant ($t(23) = -2.52, P < 0.05$). For fear component, the difference was strongly statistically significant ($t(23) = -5.93, P < 0.001$). Power motivation, however, achieved the same performance between LS1 fear component and LS3. But LS1 hope component had 25% higher accuracy than LS3 which was statistically significant according to a t-test ($t(23) = 6.87, P < 0.001$).

In terms of the differences between LS2 and LS3, LS2 had 12% lower accuracy than LS3 for affiliation motivation. A t-test showed this difference was statistically significant ($t(23) = -3.07, P < 0.01$). In the IPP, LS3 generally had better performance than LS2.

According to results from the IPP, we conclude that hope components of LS1 had better performance than fear components for achievement, affiliation and power motivation. Hope components of LS1 outperformed LS3 in power motivation, while LS3 outperformed LS1 in affiliation motivation. LS3 generally achieved better performance than LS2 in the IPP.

The conclusions were further examined in terms of their kappa statistics. As shown in Tab. 5.4, the kappa statistic of the hope component of LS1 has better performance than that of the fear components for achievement and power motivation, however, the value of the kappa statistic did not support the conclusion of affiliation motivation classification. The kappa statistic of the hope component of LS1 also had

Table 5.4: Comparison of accuracy between three subject labelling schemes on player motivation classification using player behaviour from the individual play and social network phases

Labelling scheme		***Player behaviour from the IPP***			***Player behaviour from the SNP***		
		Achievment	*Affiliation*	*Power*	*Achievment*	*Affiliation*	*Power*
LS1	*Hope*	57%±20% kappa:0.17	53%±15% kappa:-0.11	67%±14% kappa:0.27	64%±17% kappa:-0.07	65%±23% kappa:0.40	56%±22% kappa:0.10
	Fear	34%±19% kappa:-0.26	38%±19% kappa:0.02	42%±21% kappa:-0.25	47%±22% kappa:-0.01	35%±16% kappa:-0.29	63%±19% kappa:0.12
LS2		40%±17% kappa:-0.04	50%±17% kappa:0.25	39%±22% kappa:0.07	42%±12% kappa:-0.05	45%±19% kappa:0.16	46%±14% kappa:-0.01
LS3		43%±20% kappa:0.04	62%±20% kappa:0.3	42%±21% kappa:0.01	38%±20% kappa:-0.02	59%±17% kappa:0.25	40%±15% kappa:-0.11

better performance than LS3 in power motivation. Nevertheless, the kappa statistic of LS3 appeared to be almost equal to those of LS2.

As for the SNP, the performance of using player behaviour for motivation classification is shown in Tab. 5.4. In terms of hope and fear components in LS1, the hope component of LS1 had 17% and 30% higher accuracy than the fear component for achievement and affiliation motivation respectively. A t-test validated the statistical significance of these differences between achievement ($t(23) = 4.22, P < 0.001$) and affiliation ($t(23) = 7.26, P < 0.001$).

For LS1 and LS3, hope component of LS1 had 26% and 16% higher accuracies than LS3 for achievement and power motivation. A t-test indicated these differences of achievement ($t(23) = 5.57, P < 0.001$) and power ($t(23) = 3.22, P < 0.01$) were statistically significant. Fear component of LS1 had 23% higher accuracy than LS3 for power motivation with a t-test showing it to be statistically significant ($t(23) = 5.09, P < 0.001$). However, LS3 had 24% higher accuracy than the fear component of LS1 for affiliation motivation. A t-test validated the statistical significance of this difference ($t(23) = -7.18, P < 0.001$). According to LS2 and LS3, LS2 had 14% lower accuracy than LS3 for affiliation motivation with corresponding t-test result ($t(23) = -4.18, P < 0.001$).

According to results from the SNP, fear components of achievement and affiliation achieved less accuracy than the hope component of each motivation using player behaviour data. Compared to the hope component of LS1, LS3 performed worse in achievement and power motivation classification. As for the fear component, LS3 performed better in affiliation and worse in power motivation. LS3 performed better than LS2 in affiliation motivation classification.

Similarly, we further examined the kappa statistics. As we can see from the Tab. 5.4, the kappa statistic of the fear component of affiliation was much lower than hope component, but for achievement motivation, the results were similar. For hope component of LS1 and LS3, LS3 had worse performance only in power motivation classification. As for the fear component, the results of the kappa statistic were consistent with the accuracy results. Also, the kappa statistic of LS3 had a slightly better performance than LS2 in affiliation motivation classification.

Overall, motivation classification performance from player behaviour data was low. Specifically, we conclude that with a strength-related labelling scheme, the hope component of each motivation can be classified better than the fear component using player behaviour in both the IPP and SNP. Using a situation-based labelling scheme, the scheme that combined L-L and H-H has better performance. When comparing LS1 and LS3, we conclude that LS3 has better performance in affiliation motivation classification, and worse performance in achievement and power motivation, especially in the hope component.

5.3 Classifying Player Motivation from Electroencephalographic Data

5.3.1 Aim

The aim of this experiment is to determine whether an individual's motive profile can be classified by their EEG signal using our abstract mini-game. Through a series of EEG signal processing procedures, EEG data from the IPP and SNP are input to a classifier. Their classification results are compared with classification by player behaviour. In addition, we also investigate which parts of the game are most effective for assessing motivation: the IPP or SNP.

5.3.2 Hypothesis

We hypothesise that we will be able to classify motivation from EEG signals with at least the accuracy of classification using behaviour data.

5.3.3 Method

This section describes how we processed EEG data to assess subjects' motivation. A summary of this process is shown in Fig. 5.1, with explanations of each step given in the following sections.

5.3.3.1 EEG Pre-processing

The first step was to pre-process the data by filtering. Filters can be classified as finite impulse response (FIR) filters and infinite impulse response (IIR) filters. FIR filters are more stable and less likely to produce the non-linear phase distortions. Because of using time-frequency decomposition of the EEG signals, FIR filters were more suitable than IIR filters in this study. Because of a very low signal-to-noise ratio of recorded EEG frequencies above 40Hz and EEG low-frequency drift influenced by the amplifier [13], a bandpass FIR filter was used between 1-42Hz.

Interpolation is a process by which the data from bad electrodes are estimated based on the activity and locations of other electrodes. Bad electrodes are in the situations that the recorded EEG signals are either completely flat or the magnitude is much larger than is possible from a real brain signal. Interpolation is often applied on high-density recording systems. The interpolation algorithms often use a weighted distance metric. The spherical interpolation method using spherical spline surfaces was performed in EEGLAB [152].

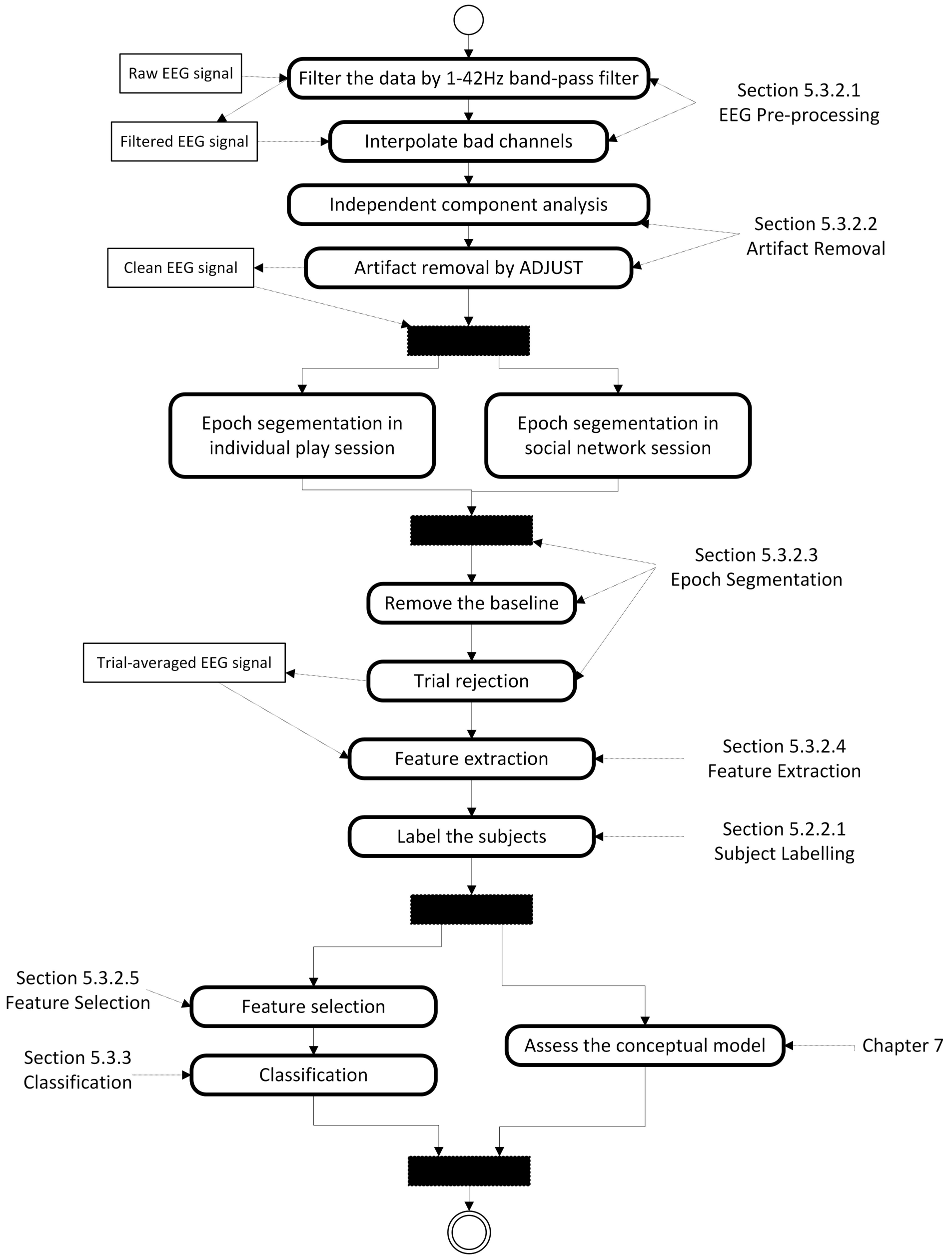


Figure 5.1: Flowchart of the EEG signal processing

Because the HD 72 device has referenced the EEG signals using the electrodes on subjects' necks during the experiment, the re-reference procedure is not required in the off-line analysis. In addition, the common average reference is not suitable after interpolating the bad channels, because the activity of the bad electrodes may interfere with the clean signals in other electrodes.

5.3.3.2 Artifact Removal

Independent component analysis (ICA) is one of the useful approaches to decompose EEG data into different independent components (ICs). However, as the manual detection of the ICs that have artifacts is time-consuming and subjective, automatic EEG artifact detection based on the joint use of spatial and temporal features (ADJUST) is proposed [153]. Four artifacts are identified by the ADJUST method: eye blinks, vertical eye movements, horizontal eye movements and generic discontinuity. The temporal and spatial features are extracted from the ICs, and the ICs that contain the artifacts are determined by the corresponding thresholds. After the ICA and ADJUST, cleaner EEG data are obtained for further data analysis. An experiment that compares three different artifact removal techniques (ADJUST, FASTER and a manual method) and identifies ADJUST as the most effective approach based on classification performance, is described in Appendix C.

5.3.3.3 Epoch Segmentation

To do the epoch segmentation for the EEG signal in the IPP, we defined the players' actions to use for time locking. The time at which players pressed the cooperate or defect button is regarded as the time=0 point. Recall from Chapter 4 that in order to record the brain activity corresponding to different types of visual feedback, there is a 500ms time interval between the player's action (button click) and the money feedback, and another 500ms interval between the money feedback and the satisfaction feedback. In addition, a sufficient buffer zone for edge artifact at the end of the epoch is required. Therefore, we decided that each trial includes the baseline from -500ms to 0s, 1.5s for the players actions, and money and satisfaction feedbacks, and another 500ms for the buffer zone. As the sampling rate of our EEG recording is 250Hz, there are thus 250Hz $\times$ 2.5s = 625 time points in each trial. In total, there are 20 trials $\times$ 4 NPCs $\times$ 64 channels $\times$ 625 time points for each subject in the IPP.

We also segmented the EEG signals into 2.5s time intervals for SNP, and again defined the players actions (button clicks) as the time=0. The money and satisfaction feedbacks do not have a time delay in the SNP, so we may have overlapping data when epoching the EEG signals from the SNP. This is not a problem for analysis because overlapping data is allowed in EEG data analysis [154], and bias will not be introduced if we do not need to do ICA afterwards. Therefore, each subject has 20 trials $\times$ 64 channels $\times$ 625 time points in SNP.

After the epoch segmentation, a mean baseline value was removed from each epoch because of the baseline differences between data epochs that may come from low-frequency drifts or artifacts. The mean baseline values are calculated from the baseline period of -500ms to 0s in each trial. The trials were visually inspected by the experimenter and the ones with obvious noise were removed.

5.3.3.4 Feature Extraction

EEG features are mainly temporal, spectral, time-frequency and spatial features. Different from temporal and spectral features, time-frequency features capture the two-dimensional complexity of the EEG signals and more task-relevant dynamics in EEG data. It also provides a flexible framework for further analysis, such as connectivity analysis, cross-frequency coupling [154].

In this work, we utilised complex morlet wavelet transforms to extract time-frequency features. We used complex morlet wavelets as follows:

$$cmw = e^{-t^2/2s^2} e^{i2\pi ft} \tag{5.1}$$

In particular, the first part of this equation $e^{-t^2/2s^2}$ is a Gaussian, and the second part of the equation $e^{i2\pi ft}$ is a complex sine wave. Where t is time, s is the standard deviation of the Gaussian part, which is defined as $s = n/2\pi f$, f is frequency (in hertz), and n refers to the number of wavelet cycles. The number of cycles of the Gaussian part defines its width, which in turn defines the width of the wavelet. Due to the trade-off between temporal and frequency precisions, we used a six-cycle

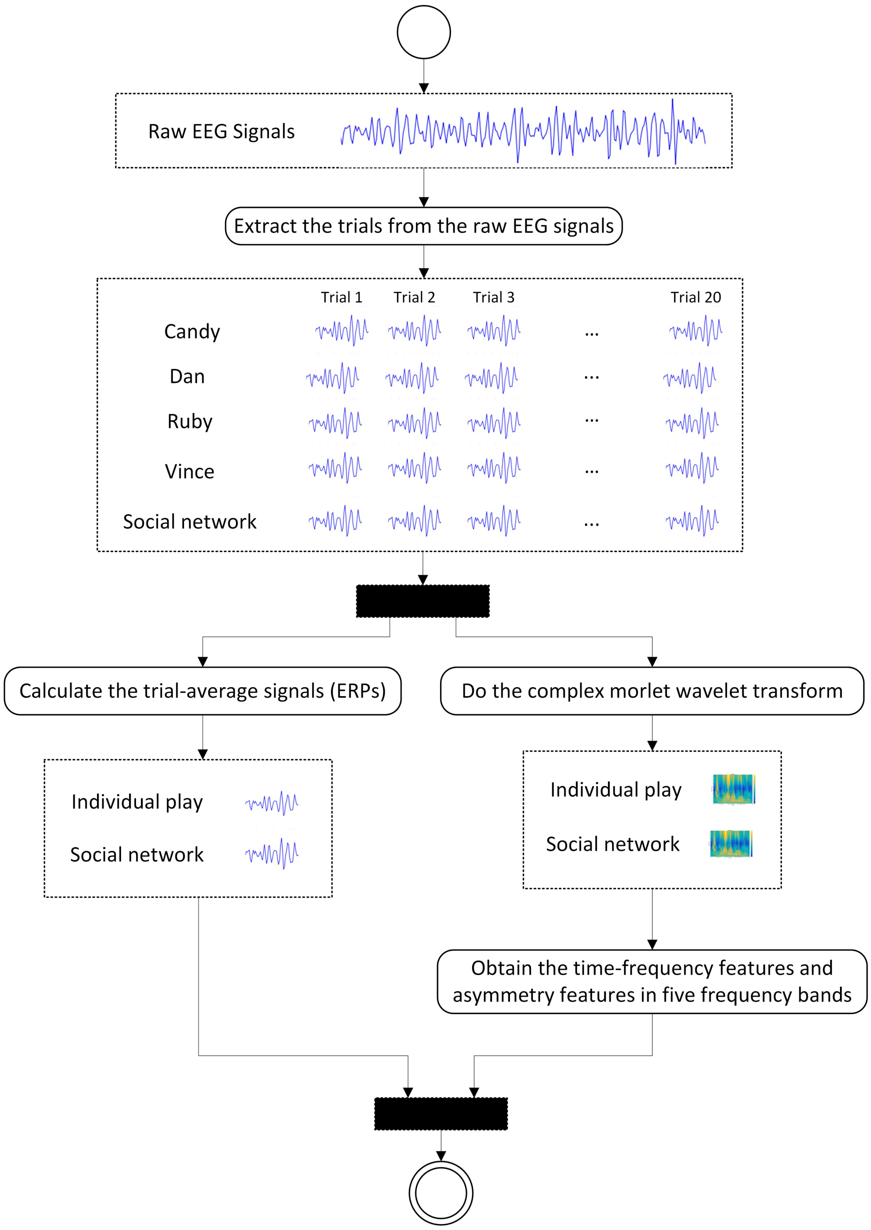


Figure 5.2: Flowchart of the epoch segmentation and feature extraction processes

wavelet in this study. The frequency increased logarithmically because we needed low-frequency information.

In addition, in order to avoid the power-law of frequency band (i.e. power decreases with increasing frequency approximating a 1/f power-law function), we used decibel (DB) normalisation [154] that is defined as in Eqn 5.2, baseline phase (-500ms to 0s) was used to do the baseline normalisation:

$$dB_{tf} = 10 \times log10(\frac{activity_{tf}}{baseline_{tf}}) \tag{5.2}$$

DB normalisation is helpful to compare results across subjects and to visualise power at different frequency bands [154]. We used the time-frequency features from five frequency bands, delta (1-3Hz), theta (4-7Hz), alpha (8-12Hz), beta (13-31Hz) and gamma (32-42Hz) in 64 channels. Thus we have a feature set that includes 5 frequency bands $\times$ 64 channels = 320 features for each condition.

As described in Fig. 5.2, twenty trials were extracted from the raw EEG signals generated when each subject plays with Candy, Dan, Ruby, Vince and their social network separately. In the next step, the signals were averaged across the trials to compute the ERPs for each phase. Also, time-frequency features were obtained using the complex morlet wavelet transform. Overall, the feature set consists of 5 frequency bands and 64 channels, in total $5 \times 64 = 320$ features for classification.

We also considered asymmetry features because there is evidence that the differences between the left and right hemisphere are associated with emotions, risk-taking and social attitudes. We used the differential asymmetry between the time-frequency features of 28 pairs of left and right electrodes excluding the electrodes in the medial region (FP1-FP2, AFP5-AFP6, AF7-AF8, AF5-AF6, AF3-AF4, AF1-AF2, F7-F8, F5-F6, F3-F4, F1-F2, FT7-FT8, FC5-FC6, FC3-FC4, FC1-FC2, T7-F8, C5-C6, C3-C4, C1-C2, TP7-TP8, CP5-CP6, CP3-CP4, CP1-CP2, PO7-PO8, PO5-PO6, PO3-PO4, PO1-PO2, POO7-POO8, O1-O2). So there are 28 pairs of electrodes and 5 frequency bands, in total $28 \times 5 = 140$ features.

5.3.3.5 Feature Selection

Correlation-based feature subset selection was employed to evaluate a subset of features. The individual predictive ability of each feature was considered, along with the degree of redundancy between them [155]. It repetitively adds features with the highest correlation with the class as long as there is not already a feature in the subset that has a higher correlation with the feature in question. In this way, it selects for subsets of features that are highly correlated with the class, and have low inter-correlation.

A BestFirst method is used to search the space of feature subsets by greedy hill-climbing, augmented with a backtracking facility. Also, the forward direction is applied to select features starting with the empty set then searches forward, and stops when there are five consecutive non-improving nodes. An experiment that compares three different feature selection techniques (correlation-based, chi-square based and wrapper method) is discussed in Appendix E. We also examined correlation-based feature subset selection and determined it to be the most appropriate approach.

5.3.4 Results and Discussion

We continued to examine whether an individual's motive profiles can be identified by their EEG signals from the mini-game. The performance of our three subject labelling schemes, using EEG signals from the IPP and SNP, is shown in Tab. 5.5. In the IPP, when comparing hope and fear components of LS1, the hope component of LS1 had 8% higher accuracy in affiliation motivation and 9% lower accuracy in achievement motivation, compared to fear component. Results of a t-test showed that the difference in achievement is statistically significant ($t(23) = -2.82, P < 0.01$), while the difference in affiliation motivation is slightly significant ($t(23) = 2.04, P < 0.05$).

As for LS1 and LS3, hope and fear components of LS1 had higher accuracies than LS3 with 9% and 18% in achievement, 8% and 8% in power respectively. T-test results indicated the difference between the fear component of achievement and LS3 is strongly significant ($t(23) = 4.93, P < 0.001$). The rest of them are statistically significant ($t(23) = 2.15, P < 0.05$ for hope of success, $t(23) = 2.51, P < 0.05$ for hope of control, $t(23) = 2.37, P < 0.05$ for fear of loss of control).

LS3 had 20%, 37% and 16% higher accuracy than LS2 in achievement, affiliation and power motivation respectively. A statistical test indicates the significance of these differences between achievement ($t(23) = -6.07, P < 0.001$), affiliation ($t(23) = -10.52, P < 0.001$) and power ($t(23) = -4.48, P < 0.001$).

According to results from the IPP, the performance of the hope component of LS1 was better than the fear component in affiliation, but worse in achievement motivation. LS1 had better performance than LS3 in achievement and power motivation. LS3 had better performance than LS2 in achievement, affiliation and power motivation classification.

The conclusions were further examined in terms of the kappa statistics. Results from Tab. 5.5 indicate that the hope component of LS1 had better performance than the fear component in affiliation, and worse performance in achievement motivation. LS1 had similar performances with LS3 in achievement and power motivation. LS3 had better performance than LS2 among three motivations.

In the SNP, we first compared hope and fear components of LS1: the hope component of LS1 had 15% higher accuracy than the fear component in affiliation motivation, with a t-test validating the statistical significance ($t(23) = 3.71, P < 0.001$). As for LS1 and LS3, hope and fear components of LS1 had 50% and 35% higher accuracies respectively than LS3 for affiliation motivation classification. The results of t-test results indicated the strong statistical significance of these differences for the hope ($t(23) = 16.18, P < 0.001$) and fear component ($t(23) = 8.10, P < 0.001$). Also, the fear component of LS1 had 8% higher accuracy than LS3 for achievement motivation, with a t-test indicating statistical significance ($t(23) = 2.38, P < 0.05$).

Finally, when comparing LS2 and LS3, LS3 had 11%, 25% and 27% higher accuracy than LS2 for achievement, affiliation and power motivation respectively. A t-test showed the differences of achievement ($t(23) = -3.83, P < 0.001$), affiliation ($t(23) = 7.81, P < 0.001$) and power ($t(23) = -8.76, P < 0.001$) are statistically significant.

According to results from the SNP, the hope component of LS1 performed better than the fear component in affiliation motivation. Also, LS1 had better performance than LS3 in affiliation motivation classification. LS3 generally outperformed LS2 for

Table 5.5: Comparison of performance between three subject labelling schemes on player motivation classification using EEG signal from the individual play and social network phases

Labelling scheme		***EEG signals from the IPP***			***EEG signals from SNP***		
		Achievment	*Affiliation*	*Power*	*Achievment*	*Affiliation*	*Power*
LS1	*Hope*	74%±18%	78%±18%	81%±15%	80%±17%	82%±14%	75%±13%
		kappa:0.42	kappa:0.61	kappa:0.53	kappa:0.6	kappa:0.51	kappa:0.19
	Fear	83%±14%	70%±20%	81%±16%	82%±17%	67%±25%	71%±13%
		kappa:0.67	kappa:0.45	kappa:0.52	kappa:0.67	kappa:0.41	kappa:0.16
LS2		45%±9%	39%±19%	57%±15%	63%±14%	57%±15%	47%±17%
		kappa:-0.02	kappa:0.07	kappa:0.26	kappa:0.34	kappa:0.31	kappa:0.13
LS3		65%±21%	76%±17%	73%±18%	74%±16%	32%±17%	74%±13%
		kappa:0.42	kappa:0.58	kappa:0.49	kappa:0.55	kappa:-0.2	kappa:0.5

player motive profiling.

According to the results of the kappa statistics, the hope component of LS1 achieved almost similar performance with the fear components. LS1 had better results than LS3 in affiliation motivation classification. LS3 had better results than LS2 for player motive profiling except for affiliation motivation.

The results from the EEG-based motive measurement for the IPP and SNP suggest that the hope and fear components of the LS1 labelling scheme generally have equal performance for motivation classification using EEG signals. The exception is the fear component of affiliation that has lower accuracy than the hope component in the SNP. Moreover, the performance of LS1 is slightly better than LS3 in two phases of the mini-game. But for affiliation motivation classification in the SNP, LS1 classifies much better than LS3. LS3 has better performance than LS2 in both phases of the mini-game.

In conclusion, when using player behaviour for motivation classification, LS3 generally outperforms the fear component of LS1, but achieves a worse performance than the LS1 hope component. As for EEG signals, LS3 has lower accuracies than LS1 for achievement and affiliation motivation. On the other hand, LS2 generally achieves the worst classification performance than the other two labelling schemes using player behaviour and EEG signal. Thus we will examine only the classification performance of LS1 and LS3 to see the differences between using player behaviour

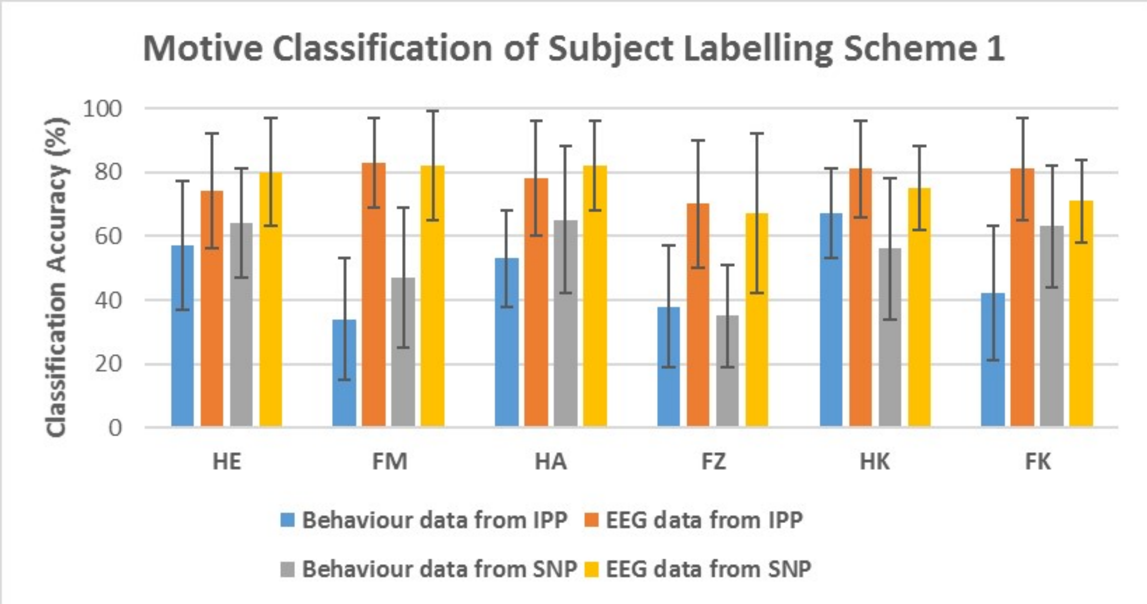


Figure 5.3: Motivation classification performance for average, above and below subject labelling scheme (LS1) using behaviour data and EEG data in IPP and SNP

and EEG signals for player motivation classification.

Subsequently, we compared the classification performance between player behaviour and EEG signals from the IPP and SNP, in order to see the effectiveness of our proposed EEG-based motivation measurement. The results for LS1 are depicted in Fig. 5.3. An independent t-test was applied on classification accuracies to see if there are any significant differences between different groups. First, we compared the performance between behaviour data and EEG signals in the IPP. The mean accuracies using EEG signal increase were 16%, 49%, 25%, 32%, 14% and 39% compared to the mean accuracies using player behaviour for the six motivation variables. An independent t-test demonstrated the statistical significance of the improvements on hope for success ($t(23) = 4.20, P < 0.001$), fear of failure ($t(23) = 14.71, P < 0.001$), hope for social acceptance ($t(23) = 7.52, P < 0.001$), fear of rejection ($t(23) = 8.15, P < 0.001$), hope for control ($t(23) = 5.01, P < 0.001$) and fear of loss of control ($t(23) = 10.3, P < 0.001$). Results indicated that classification using EEG signals outperforms the classification using player behaviour.

The classification performance between player behaviour and EEG signals from the IPP were also examined using the kappa statistics. Results from Tab. 5.4 and Tab. 5.5 show that the kappa statistics of classification using EEG signals had better results than the classification using player behaviour, which confirms that EEG-based motive profiling outperforms bebaviour-based motive profiling.

Next, we examined the classification performance between player behaviour and EEG signal in the SNP. The mean accuracies using EEG signal improved 16%, 35%, 17%, 31%, 19% and 8% compared to the mean accuracies using player behaviour for six motivation respectively. An independent t-test indicated that the differences between hope for success ($t(23) = 4.66, P < 0.001$), fear of failure ($t(23) = 8.90, P < 0.001$), hope for social acceptance ($t(23) = 4.46, P < 0.001$), fear of rejection ($t(23) = 7.34, P < 0.001$), hope for control ($t(23) = 5.31, P < 0.001$) and for fear of loss of control ($t(23) = 2.47, P < 0.05$) are statistically significant. Results from the SNP confirm that the EEG signal classification outperforms the player behaviour classification.

Results of the kappa statistics showed that motive classification using EEG signals outperformed motive classification using player behaviour for the hope and fear components of achievement and affiliation motivation. This further confirms that the EEG signal classification outperforms the player behaviour classification.

Finally, we assess the classification performance between the IPP and SNP. Player behaviour from the IPP had 11% higher accuracy than player behaviour from the SNP for hope for control. An independent t-test indicated this is statistically significant ($t(23) = 2.94, P < 0.001$). However, player behaviour from the SNP had 13%, 12% and 21% higher accuracies than player behaviour from the IPP for fear of failure, hope for social acceptance and fear of loss of control respectively. A t-test indicated that the differences between fear of failure ($t(23) = -3.33, P < 0.001$) and hope for social acceptance ($t(23) = -3.06, P < 0.001$) are statistically significant, and the difference of fear of loss of control is strongly significant ($t(23) = -5.11, P < 0.0001$). The kappa statistics also showed that player behaviour from the IPP outperformed the player bahviour from the SNP for hope for control, and player behaviour from the SNP outperform player behaviour from the IPP for fear of failure, hope for social acceptance and fear of loss of control.

EEG signals from the IPP had 6% and 10% higher accuracy than EEG signals in the SNP for hope for control and fear of loss of control respectively. An independent t-test showed the statistical significance for hope for control ($t(23) = 2.11, P < 0.05$) and fear of loss of control ($t(23) = 3.53, P < 0.001$). The kappa statistics of EEG signals from the IPP also had better performance than EEG signals in the SNP for hope for control and fear of loss of control.

In terms of LS3, Fig. 5.4 illustrates the classification performance using player behaviour and EEG signals from the IPP and SNP. In the IPP, the mean classification accuracies when assessing achievement, affiliation and power motivation from EEG signals increased by 22%, 15% and 31% respectively, compared to the mean classification accuracies using player behaviour data. An independent t-test showed the difference in mean accuracies between the classification of EEG signals and player behaviour data is statistically significant: for achievement motivation ($t(23) = 5.46, P < 0.001$) as well as for affiliation ($t(23) = 4.03, P < 0.001$) and power motivation ($t(23) = 7.66, P < 0.001$). Results of the kappa statistics also showed that in the IPP, player motive classification using EEG signals outperformed player motive classification using player behaviour for achievement, affiliation and power motivation.

In the SNP, the mean classification accuracies using EEG signals improved 23% and 26% compared to the classification using player behaviour for achievement and power motivation respectively. An independent t-test indicated the statistical significance of the improvements for achievement ($t(23) = 8.59, P < 0.001$) and power ($t(23) = 8.92, P < 0.001$). In terms of the affiliation motivation classification, classification accuracy using behaviour data was 29% higher than the accuracy using EEG data. An independent t-test showed the differences in mean accuracies ($t(23) = -8.06, P < 0.001$) are statistically significant. In terms of the kappa results, the performance of classification using EEG signals was better than classifi-

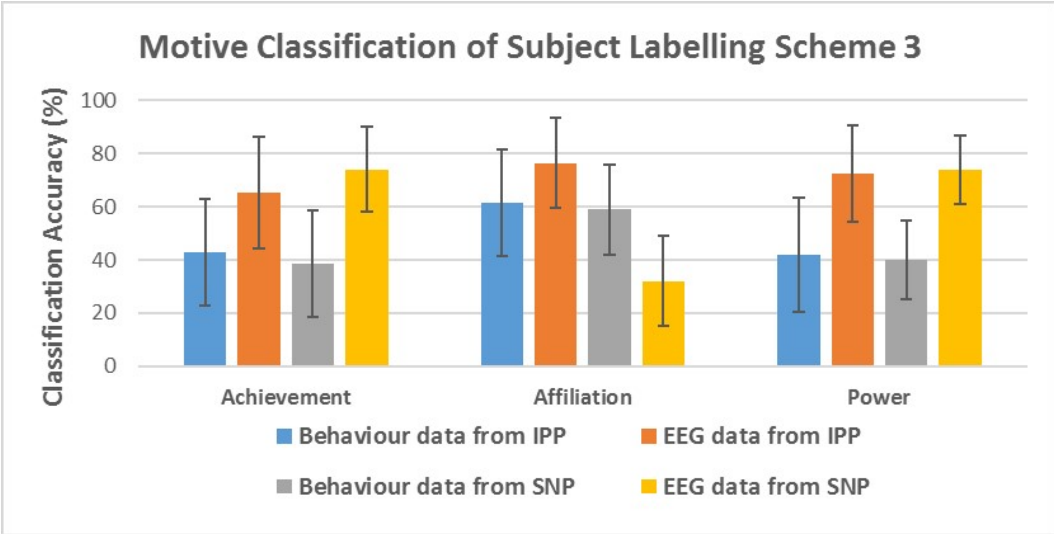


Figure 5.4: Motivation classification performance for H-L, L-H and other subject labelling scheme (LS3) using behaviour data and EEG data in IPP and SNP

cation using player behaviour for achievement and power motivation, but worse for affiliation motivation.

Moreover, when comparing the performance between the IPP and SNP, we see that affiliation classification using EEG signals from the IPP outperformed classification from data collected during the SNP by 44.3%. An independent t-test indicated the significance of the conclusion ($t(23) = 13.36, P < 0.001$). The kappa results also showed that EEG signals from the IPP had better classification performance than EEG signals from the SNP for affiliation motivation.

In conclusion, EEG data generally outperforms player behaviour for motivation classification, indicating EEG technology is a promising way to measure player motivation. As for LS1, the hope component of motivation has better performance than the fear component when using player behaviour, but achieves the same level of performance using EEG signals except for affiliation motivation. In addition, LS3 has better performance than the fear component, but worse performance than the hope component of LS1 using player behaviour. In EEG signals, LS1 outperforms LS3 in achievement in both the IPP and SNP, and affiliation motivation in the SNP. In LS3, EEG signals from the SNP have lower classification performance for affiliation motivation than EEG signals from the IPP.

5.4 General Discussion

In this chapter, three kinds of data collected from the experiment: MMG, behaviour and EEG data, have been analysed. Furthermore, the effectiveness of using EEG signal to profile player motivation has been verified. In terms of MMG data, three subject labelling schemes have been proposed according to the output of the MMG test. This provides the ground-truth to label subjects for analyzing behaviour and EEG data. For behaviour and EEG data analysis, KNN is utilized as the classifier, and classification performance between behaviour-based and EEG-based motive profiling have been compared. Overall, results support the hypothesis that EEG-based player motive profiling is a promising approach and has better performance than behaviour-based player motive profiling.

We extracted time-frequency features and asymmetry features to classify player motive profiles. For LS3, the highest mean classification accuracy of 76% (kappa=0.58) in the IPP, and of 74% (kappa=0.55) in the SNP were reached. The relationship between emotion and motivation was illustrated in studies of Elliot et al. [156] and Knyazev et al. [110], which shows that positive emotion relates to approach motivation, and negative emotion relates to withdrawal motivation. In EEG-based emotion studies, time-frequency and asymmetry features have been employed to identify emotion states effectively. Li et al. used time-frequency features as part of their feature set to classify positive and negative emotion, by using automatic feature selection methods, the highest mean accuracy for DEAP dataset is 59.06% and for SEED dataset is 83.33% [37]. This classification performance is slightly higher than our method, which may be due to the wide range of features types in Li et al.'s study. Moreover, asymmetry features have also been employed to classify positive, neutral and negative emotion, the best average classification accuracies of 69.67% and 91.07% have been achieved on the DEAP and SEED datasets [99]. The reason for their higher classification performance is perhaps because of the advanced feature selection and classification approach.

This chapter provides a preliminary analysis that implies EEG technology could be a promising way to profile player motive. In the future, more comprehensive studies of different types of EEG features and the state of art data analysis methods could be investigated to improve the performance of EEG-based motive profiling.

Intra- and inter-subject variability were not considered in this work, because the contributions of this work focuses on proposing three subject labelling schemes and examining the possibilities of using player behaviour and EEG signals to classify these subject groups. However, individuals may have different aspects of achievement, affiliation and power motivation, and player motive profiles may also drift due to various factors. This work focuses on classifying players from their dominant profile only. Further work could address hybrid profiles and profile changes.

5.5 Conclusion

In this chapter, we proposed three labelling schemes: one that considers the hope and fear components of motivation independently (LS1), and two that combine the hope and fear components of each motivation (LS2 and LS3). We found that both LS1 and LS3 can be efficient for assessing motivation in different ways.

The results from this chapter are promising indicators that we can assess player motivation from EEG data while people are engaged in a game. In addition, it appears that assessment from EEG data can be more accurate than assessment from data about player behaviour. Differences in classification results between the IPP and SNP indicate that the design of the game has a significant role to play in the ability to assess motivation from brain signals. The next chapter will investigate this finding in more detail by examining specific player behaviour and EEG features from specific points in the game.

Chapter 6

Analysing the Design of Our Mini-game for Player Motive Profiling

6.1 Introduction

The previous chapter provided evidence that EEG can be a promising way to assess player motivation when players play our game. Motivation classification from EEG data has higher accuracy than the classification from player behaviour data. In this chapter, we further examine the use of our mini-game for player motive profiling. This will be done using specific features from player behaviour and EEG data to investigate the design of the mini-game.

As described in Chapter 3, we proposed non-player characters (NPCs) to suppose player motive profiling by detecting cognitive and emotional phenomena. Our NPCs have different play strategies, money and satisfaction features. The play strategies of NPCs assist in the distinction between different player motive profiles. The money and satisfaction features of NPCs have the potential to evoke risk-taking and social attitudes respectively. In addition, the interactions between players and NPCs in the IPP and SNP are hypothesised to reveal their risk-taking and social attitudes differently to further help identify player motive profiles. Thus, player behaviour and EEG data collected from the experiment are analysed in this chapter to examine the design of the NPCs and game scenario for identifying player motive profiles and related risk-taking and social attitudes. Additional supporting results are presented in Appendix D.

Section 6.2 of this chapter analyses the effectiveness of the play strategies of NPCs for identifying motivation variables using the IPP and SNP. Section 6.3 presents an analysis of the two features of our NPCs (money and satisfaction) for assessing motivation via EEG signals. The effectiveness of the IPP and SNP for assessing motivation is summarised in Section 6.4.

6.2 Analysing Play Strategies of Non-player Characters for Assessing Motivation

As described in Section 3.3.3, four classic PD game strategies were used in our NPCs to best aid distinction between player motivation profiles. It is hypothesized that the design of these NPCs are appropriate for assessing achievement, affiliation and power motivation. Also, we hypothesized that two game phases (the individual play phase and social network phase) are suitable for examining player motivation. This section examines these hypotheses and the effectiveness of the mini-game for assessing motivation. First, correlation analysis is used to identify the relationships between motivation variables and player behaviour with each NPC in the IPP and SNP. Further, multiple linear regression is employed to model motivation from player behaviour in the IPP and SNP. Results indicate that player behaviour from specific NPCs have relationships with motivation variables. Also, player behaviour from the IPP and SNP can be used to predict motivation variables. However, the results also suggest several limitations. For example, several motivation variables cannot be assessed using player behaviour from the game.

6.2.1 Aim

The aim of this section is to assess whether the play strategies of NPCs in our mini-game are appropriate for differentiating player behaviour that ultimately contributes to player motive profiling. To achieve the goal, two research questions are answered in this section. First, we aim to assess whether different play strategies of NPCs contribute to differentiation between player motive profiles. Secondly, we assess whether different game phases (individual play and social network play) contribute to differentiation between player motive profiles.

6.2.2 Hypothesis

We hypothesise that play strategies of NPCs in the mini-game are appropriate for differentiating between player motive profiles. Specifically, Cooperator Candy is proposed for cooperation by achievement and affiliation motivated players, and for exploitation by power motivated players. Vengeful Vince is proposed for cooperation by achievement and affiliation motivated players. Random Ruby's strategy represents a risk-taking challenge potentially preferred by power motivated players. Defector Dan, on the other hand, may be preferred by affiliation motivated players for cooperation. In addition, we hypothesise that NPCs incoporated in both the IPP and SNP are appropriate for distinguishing player motive profiles.

6.2.3 Method

Correlation analysis Correlation analysis is used to identify the relationships between motivation variables and player behaviour with different NPCs. Correlation analysis is a statistical method that measures the strength of a linearly increasing or decreasing relationship. Sample correlation coefficient is calculated and denoted by r.

$$r = \frac{\sum_{i=1}^{n} X_i Y_i - n\overline{XY}}{\sqrt{(\sum_{i=1}^{n} X_i^2 - n\overline{X}^2)(\sum_{i=1}^{n} Y_i^2 - n\overline{Y}^2)}} \tag{6.1}$$

Correlation coefficient r represents the relationship between two variables. If r is close to zero, there is no tendency for the change of one variable corresponding to the other variable. The correlation coefficient is always a value between 1 and -1. A value of 1 indicates a strong positive relationship, while a value of -1 means a strong negative relationship. Generally, the relationship is considered strong when the absolute value of r is above 0.7, moderate when r is between 0.4 and 0.7, weak when r is between 0.3 and 0.4, and there is no relationship when r is less than 0.3. Therefore, we set the criteria $|r| > 0.3$ for determining if there is a relationship between motivation variables and player behaviour with various NPCs.

Multiple linear regression To understand and model motivation from player behaviour, it is important to understand the internal relationships between motivation and behaviour. Although there are many modelling approaches in the statistical fields, regression is a useful and straightforward way for predicting an output response variable based on input predictor variables. Moreover, the advantage of the regression method is that it can clearly show what kind of relationships exist between the input and output variables and how strong they are. Among them, linear regression is the simplest way to investigate the relationships, but the linear regression model assumes that this is a straight-line relationship, which sometimes may not be the case.

In some situations, the true relationship is far from linear, for example, the change in the response variable Y due to a one-unit change in one of the predictor variables X_i on the basis of the value of the other predictor variable X_j. In statistics, this is referred to as an interaction effect. The regression model can be extended for interaction effects by including an interaction term, which is computed by the multiplication of these two predictor variables X_iX_j. This means that adjusting X_j will change the impact of X_i on Y.

The other way to extend the linear model is to incorporate non-linear relationships using polynomial regression. If the data suggests a curved relationship or quadratic shape, it is better to add these non-linear associations to the model by including transformed versions of the predictors X_i^2. It should be noted that this is still a linear model despite having a polynomial function of the predictors. With this knowledge, our intention was to model the motivation from player behaviour data by regression methods.

A multiple linear regression model can be written mathematically as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p + \epsilon \tag{6.2}$$

Where X_i represents the ith predictor and β_i quantifies the associations between that variable and the response. The β_i is interpreted as the average effect on the response Y of a one unit increase in X_i with all the other predictors fixed [126].

Firstly, we need to check whether there is any relationship between the response and predictors by testing the null hypothesis:

$$H_0 : \beta_1 = \beta_2 = ... = \beta_p = 0 \tag{6.3}$$

versus the alternative

$$H_\alpha : at\ least\ one\ \beta_i\ is\ non - zero \tag{6.4}$$

The hypothesis is tested using the F-test

$$F = \frac{(TSS - RSS)/P}{RSS/(n - p - 1)} \tag{6.5}$$

where $TSS = \sum(y_i - \bar{y})^2$ is the total sum of squares and $RSS = \sum(y_i - \hat{y}_i)^2$ is the residual sum of squares. If there is no relationship between the response and the predictors, the value of the F-test is close to 1, On the other hand, it is expected that the value will be greater than 1. In order to determine whether to reject the hypothesis by the F-test, the values of n and p need to be taken into consideration. If n is large, a small value of the F-test can be used to reject H_0, whereas when n is small, a larger value of the F-test is required to reject H_0. In practice, the p value associated with the F-test is usually computed to determine whether or not to reject H_0. A small p value indicates that at least one of the predictors is associated with the response.

Furthermore, we need to determine which predictors are associated with the response. This process is referred to as variable selection. There are three classic approaches for stepwise variable selection: forward selection, backward selection and mixed selection. Forward selection begins with the null model that contains an intercept, but no predictors. Then, it adds the new variables into the null model that results in the lowest RSS. Backward selection starts with all variables in the model and removes the variable with the largest p value, the variable that is the least statistically significant. Mixed selection is a combination of forward and backward selection. It begins with a null model, then continues to perform forward and backward steps until all variables in the model have a sufficiently low p value, and all variables outside the model would have a large p value if added to the model.

After completing the stepwise regression steps, our final model is analysed with all the selected variables and their corresponding coefficients. We ensured all the selected variables have the p value less than 0.05, except for the variables in the interactive term. According to the hierarchical principle, if we include an interaction term in the model, we should also include the individual variables, even if the p values associated with their coefficients are not significant. Two common measurements of model performance are the residual error and R^2. R^2 represents the proportion of variance in Y that can be explained using X. R^2 is calculated using the following equation:

$$R^2 = \frac{TSS - RSS}{TSS} \tag{6.6}$$

Table 6.1: Correlation coefficients between motivation variables and player behaviour with NPCs in the individual play phase

	P^C	P^D	P^R	P^V
Hope for Success	**0.43** $*$	**-0.31**	0.16	-0.1
Fear of Failure	**-0.31**	0.09	-0.18	0.07
Hope for Control	-0.04	-0.15	-0.05	-0.23
Fear of Loss of Control	0.19	**0.34**	**0.43** $*$	0.19
Hope for Social Acceptance	-0.28	**-0.34**	-0.02	**-0.41**
Fear of Rejection	0.02	-0.03	0.24	-0.14

Table 6.2: Correlation coefficients between motivation variables and player behaviour with NPCs in the social network phase

	N^C	N^D	N^R	N^V
Hope for success	0.23	**0.44** $*$	0.27	0.03
Fear of failure	**-0.31**	0/26	0.20	0.29
Hope for control	-0.27	**0.43** $*$	0.11	0.08
Fear of loss of control	-0.08	0.26	0.22	-0.04
Hope for social acceptance	0.11	0.02	**-0.39**	-0.18
Fear of rejection	-0.20	0.27	0.33	**0.52** $*$

An R^2 value that is close to 1 indicates that a large proportion of the variability in the response has been explained by the regression. The value of R^2 close to 0 indicates that the regression did not explain much of the variability in the response. The mean squared error (MSE) is another way to measure the model fit. It is the average number that the response will deviate from the true regression line. The equation for MSE is:

$$MSE = \frac{1}{n} \sum \sqrt{(y_i - \hat{y}_i)^2} \tag{6.7}$$

If the estimated predictions using the model are very close to the true outcome values, then the MSE will be small, which demonstrates that our model fits the data very well. If the estimated prediction is far from the true values, the MSE will be quite large, indicating that the model does not fit the data very well.

6.2.4 Results

Tab. 6.1 shows the correlation coefficients between player behaviour (specifically P^C, P^D, P^R, P^V) with NPCs and motivation variables. The correlation coefficients that indicate the relationship between two variables ($|r| > 0.3$) are highlighted in bold. $*$ means that the relationship between two variables are statistical significant ($P < 0.05$). We can see from the table that the probability of cooperation with Candy positively relates to hope for success. In addition, the probability of cooperation with Ruby is positively related to fear of loss of control. We further explore the use of NPCs in assessing motivation in the SNP. Tab. 6.2 lists correlation coefficients between player behaviour (e.g. N^C, N^D, N^R, N^V) with NPCs and motivation variables. As shown in the table, the percentage of Dan chosen in social networks positively relates to hope for success and hope for control. Lastly, the percentage of Vince in social networks positively relates to fear of rejection.

Multiple linear regression is used to model motivation from player behaviour with NPCs. Motivation data from the MMG test has six motivation variables, which are regarded as the response. The requirement for using a linear regression model is that the response should be normally distributed. Thus, we used the Kolmogorov-Smirnov test (KS test) to examine the distribution of our six motivational variables from the MMG test. The results showed that these six variables have normal distributions, which means it is appropriate to employ linear regression for motivation modelling. An experiment was performed between player behaviour in the IPP and motivation variables. This helps us to examine whether the design of the IPP is appropriate for player motive profiling.

The mixed stepwise method was used to select relevant predictors. Modelling mainly focused on linear terms, and if these could not represent the relationships, then interaction and quadratic terms were added. All the important variables were included in the model in terms of the principle of regression. The probability of cooperation with Cooperator Candy, Defector Dan, Random Ruby and Vengeful Vince were input into the regression model as the predictors. Due to the different scale

Table 6.3: Characteristics of regression models using player behaviour in individual play phase to predict motivation profile

	P-value	R^2	***MSE (%)***	***Candy***	***Dan***	***Ruby***	***Vince***
Hope for Success	<0.05	0.3	19.3	✓	✓		
Fear of Failure	<0.05	0.6	13.9		✓	✓	✓
Hope for Control	>0.1	0.3	17.7				
Fear of Loss of Control	<0.05	0.2	17.4			✓	
Hope for Social Acceptance	<0.05	0.5	12.8	✓	✓		✓
Fear of Rejection	<0.1	0.2	24.2	✓			

Table 6.4: Characteristics of regression models using player behaviour in social network phase to predict motivation profile

	P-value	R^2	***MES(%)***	***Candy***	***Dan***	***Ruby***	***Vince***
Hope for Success	<0.05	0.2	20.7		✓		
Fear of Failure	=0.05	0.5	15.7	✓		✓	✓
Hope for Control	<0.005	0.2	20.8		✓		
Fear of Loss of Control	<0.01	0.3	16.6	✓	✓		
Hope for Social Acceptance	<0.05	0.4	14.4		✓	✓	
Fear of Rejection	<0.05	0.3	25.8				✓

between motivational variance and the probability of cooperation, the probability of cooperation was multiplied by 100.

In the IPP, different subjects have various play strategies depending upon which characters they are playing with. They have different probabilities of cooperation with Cooperator Candy, Defector Dan, Random Ruby and Vengeful Vince. We used regression to find the relationships between player behaviour with NPCs and the motivation variables. As shown in Tab. 6.3, the p values indicate that most of the motivation regression models are statistically significant except for the hope for control variable. This means that the hope for control variable cannot be learned from player behaviour in the IPP. The R^2 show the variability of motivation values that can be explained by the player behaviour in the IPP. We can see from the Tab. 6.3, fear of failure and hope for social acceptance have the highest R^2 value with both above 0.5. However, for fear of loss of control and fear of rejection, the R^2 values are relatively small with the value around 0.2. This may indicate that our design of the IPP can reveal fear of failure and hope for social acceptance the best among the six variables, while fear of loss of control and fear of rejection are revealed the least well and the hope for success falls in the middle.

In addition, the MSE shows the random error that is included in the regression model when fitting the data. This is the other indicator that demonstrates how the regression model fits the data and how our game reveals players' motivation values. Tab. 6.3 shows that five motivation variables have mean MSE values less than 20%, which indicates the regression models fit the data properly. P^C, P^D, P^R and P^V represent the probability of player cooperation with Cooperator Candy, Defector Dan, Random Ruby and Vengeful Vince. We indicate the characters that are included in each of the regression models in Tab. 6.3. Player behaviour with Candy and Dan contributed to hope for success, player behaviour with Dan, Ruby and Vince related to fear of failure. For fear of loss of control, player behaviour with Ruby was significant. Player behaviour with Candy, Dan and Vince were relevant to hope for social acceptance, whereas fear of rejection depended on player behaviour with Candy.

In the SNP, players can decide how to organise their social networks by choosing to incorporate their preferred characters from Cooperator Candy, Defector Dan, Random Ruby and Vengeful Vince. The regression was performed between the percentage of different characters in subjects' networks (N^C, N^D, N^R, N^V) and the motivation variables. Tab. 6.4 shows statistical characteristics of the regression models. All of the p values are less than or around 0.05 (except fear of loss of control that is $p < 0.01$) which means the relationships between player behaviour in the SNP and motivation values are statistically significant. The R^2 of fear of failure and hope for social acceptance are higher than the remaining motivation variables, which indicates that the SNP reveals fear of failure and hope for social acceptance more successfully. Hope for success and hope for control have R^2 values around 0.2, which may mean our game cannot assess these two variables very well.

We conclude with the player variables that are included in each of the SNP regression models in Tab. 6.4. Fear of failure has player behaviour with three characters included to the regression models, fear of loss of control and hope for social acceptance have two variables, while the hope for success, hope for control and fear of rejection only have one variable.

According to MSE, as shown in Tab. 6.4, column 4, hope for success, hope for control and fear of rejection have MSE above 20%. In particular, fear of rejection has 25% MSE, which demonstrates that the SNP may not reveal motivation as well as the IPP. For the rest of the motivation variables, the MSEs are around 15%, suggesting a better model fit.

6.2.5 Discussion

In this section, we used correlation analysis to assess the relationships between the play strategies of each NPC and player motivation variables. Results imply in the IPP that the design of Candy contributes to assessing achievement motivation (hope component) and the design of Ruby contributes to assessing power (fear component). Moreover, in the SNP, the design of Dan contributes to assessing achievement (hope component) and power (hope component), and the design of Vince contributes to assessing affiliation (fear component). Since the results indicated the design of NPCs had possibilities for measuring player motivation via player behaviour, we further explored the use of NPCs in assessing motivation through the IPP and SNP.

Multiple linear regression results from the IPP and SNP supported our hypothesis that different characters contribute to differentiating motives in different ways. Specifically, we can conclude from Tab. 6.3 that most motivation variables can be learned from player behaviour in the IPP, except hope for control. Moreover, by examining the variability of motivation variables that can be explained by player behaviour in the IPP, we found that fear of failure and hope for social acceptance can be modelled better than the rest of variables. Results also imply that in the IPP, the design of Candy contributes to assessing hope for success, hope for social acceptance and fear of rejection; and the design of Dan contributes to assessing hope for success, fear of failure, hope for social acceptance. The design of Ruby contributes to assessing fear of failure and fear of loss of control, while the design of Vince contributes to assessing fear of failure and hope for social acceptance. Results indicate the design of NPCs have possibilities for measuring player motivation via player behaviour in the IPP.

Results in Tab 6.4 show that the design of Candy in the SNP contributes to identifying fear of failure and fear of loss of control, while the design of Dan contributes to identifying hope for success, hope for control, fear of loss of control and hope for social acceptance. The design of Ruby contributes to identifying fear of failure and hope for social acceptance, and the design of Vince contributes to identifying fear of failure and fear of rejection. The variability of fear of failure and hope for social acceptance can be explained better than the other motivation variables using player behaviour in the SNP. This supports our hypothesis that the design of NPCs have the potential to assess player motivation in the SNP. When comparing the use of play strategies of NPCs in the IPP and SNP from Tab. 6.1 and Tab. 6.2, we conclude that the IPP is more effective at assessing player motivation than the SNP using player behaviour from the game.

These results with player behaviour identify the importance of using different NPCs to assess player motive profiles. However, there are still several motivation variables that cannot be learned from the results. One reason for this is perhaps our game design requires further improvements. Another reason may be the player behaviour provides limited information for assessing player motivation, while the advantage of EEG-based motive measurement is that EEG signals provide continuous and rich information about the human mind. In the next section, we use EEG signals to examine the money and satisfaction features of NPCs in order to assess the mental states of player motive profiles.

6.3 Analysing Features of Non-player Characters for Assessing Motivation

Our NPC design has two features: money and satisfaction, as depicted in Fig. 3.4. The money feature is designed to examine the risk-taking and the satisfaction feature is designed to examine social attitude. Also, the play strategies of NPCs are proposed to differentiate players' risk-taking and social attitudes. This section examines the value of different NPC features (money and satisfaction) and play strategies of NPCs for assessing motivation. We analyse EEG features discussed in the existing literature to understand how our NPC design can be used for assessing social and risk-taking attitudes. A t-test is computed to determine the significance of the differences between EEG features for the H-L and L-H situations of each motivation. Results showed that the money feature can be used to reveal risk-taking, and the satisfaction feature can be used to evoking social attitude. Results showed that Candy emerged as the least useful character, while Ruby and Vince are good choices for evoking social attitude, Dan, Ruby and Vince are appropriate for evoking risk-taking attitude.

6.3.1 Aim

The aim of this experiment is to examine how money and satisfaction features are able to reveal risk-taking and social attitudes, which are key aspects of achievement, affiliation and power motivation. Two research questions are answered in this section: The first question is to assess whether different NPC dimensions (money and satisfaction) contribute to differentiation between players' risk-taking and social attitudes. The second question is to assess whether the play strategies of NPCs contribute to differentiation between players' risk-taking and social attitudes.

6.3.2 Hypothesis

Our NPCs have two features: money and satisfaction. The money feature represents a tangible, valuable item in our daily life. It is treated as monetary rewards in the mini-game, which is hypothesised to assist with the differentiation of risk-taking attitudes of players with different motives.

The satisfaction feature, on the other hand, is associated with social satisfaction about interactions between players and NPCs. It is treated as a state of friendship in the mini-game. We hypothesise that it will enable us distinguish between social attitudes of players with different motives.

6.3.3 Method

As described in Sections 5.2.3 and 5.2.4, after pre-processing, recordings were segmented in 20 trials in the IPP. Each trial has a 2.5s time segment, including baseline (-500ms to 0s), time=0s for onset of players' actions, 2s for onset of money, satisfaction feedback, and buffer zone. In order to understand mental states, in particular actions and responses, we divided the EEG analysis into specific 500ms time windows for action, money feedback and satisfaction feedback. Specifically, the action starts from 0s to 500ms, money feedback occurs from 600ms (including average system delay) to 1.1s, and satisfaction feedback occurs from 1.2s to 1.7s in each trial. Features were extracted from these time windows without overlapping for analysing risk-taking and social attitude when players made actions, and received money and satisfaction feedback. Features extracted from EEG signals can be categorised into three groups: temporal, time-frequency and asymmetry features.

Time-frequency features were calculated by complex wavelet transformation and decibel normalisation was utilised. The detail of the processing method is described in Section 5.3.2. Time-frequency features were divided into five frequency bands: alpha/mu band (8-12Hz), theta band (4-7Hz), beta band (13-31Hz) and gamma band (32-42Hz). According to the international 10-10 system, the frontal region is electrodes FP1, FP2, FPz, AFP5, AFP6, AF7, AF3, AF1, AFz, AF2, AF4, AF6, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8; the pre-frontal region is electrodes FP1, FP2, FPz, AF7, AF5, AF3, AF1, AFz, AF2, AF4, AF6 and AF8; the ACC is electrodes Fz, FCz and Cz; the parietal region is PO7, PO5, PO3, PO1, POz, PO2, PO4, PO6, PO8, POO7, POO8, O1, O2 and Oz; the temporal region is FT7, T7, TP7, FT8, T8 and TP8.

Asymmetry features were derived from the differences between the left and right hemisphere, thus a positive value means greater left than right, and a negative value

Table 6.5: Features extracted for identifying mental indicators of motive profile

Mental State	***Feature***	***Brain region***	***Category***
Social	Mu band	ACC	Time-frequency feature
	Alpha band	Frontal	Asymmetry
Risk	Alpha band	Pre-fronatl	Asymmetry
	Theta-beta ratio	ACC	Time-frequency feature
	ERN	ACC	Temporal
	MFN	ACC	Temporal
	P300	ACC	Temporal

means greater right than left. The electrode pairs for frontal alpha are FP1-FP2, AFP5-AFP6, AF7-AF8, AF5-AF6, AF3-AF4, AF1-AF2, F7-F8, F5-F6, F3-F4, F1-F2, FT7-FT8, FC5-FC6, FC3-FC4, FC1-FC2, T7-F8, and for prefrontal alpha are FP1-FP2, AFP5-AFP6, AF7-AF8, AF5-AF6, AF3-AF4, AF1-AF2.

EEG data were epoched in three types of segment depending on the temporal features being analysed. For the analysis of event-related negativity (ERN), the mean amplitude was calculated in segments of 100ms from 0 to 100ms time-locked to the onset of money and satisfaction feedbacks. For medial frontal negativity (MFN), we derived mean amplitude from 200ms to 300ms time-locked to the action and feedbacks onset, while P300 was also calculated as the mean value of the time segment of 300ms and 400ms to the feedback onset. Following the EEG-based risk-taking literature, all temporal features were computed in the ACC area (Fz, FCz and Cz).

As presented in Tab. 6.5, mu band in the ACC and frontal alpha asymmetry were computed to be indicators of social attitudes. Prefrontal alpha asymmetry, theta-beta ratio, ERN, MFN and P300 in ACC were calculated as EEG features for risk-taking attitudes.

According to the regression analysis on motivation and player behaviour in the IPP, play with certain NPCs was evaluated to be more relevant to the H-L or L-H situation of each motivation. We summarise this in Tab. 6.6. As shown in Tab. 6.6, play with Candy and Dan was chosen to study H-L achievement, while the study of L-H achievement used the play with Dan, Ruby and Vince. For affiliation, our study of the H-L component used the play with Candy, Dan and Vince, while only

Table 6.6: Hypothesis about using the conceptual model to evaluate risk-taking and social attitudes for each motivation related to the behaviour. The important part of the game is selected from the regression analysis of in-game behaviour developed in Section 6.2.

Motivation		***Important Part of game***	***Attitude***	***Features***
Achievement	*HL*	P_C P_D	Low social	high A_{mu}, greater right than left F_α
	LH	P_D P_R P_V	medium risk	medium A_{TBR}, medium PF_α, medium A_{MFN} medium A_{ERN} and medium A_{P300}
Affiliation	*HL*	P_C P_D P_V	High social	low A_{mu}, greater left than right F_α
	LH	P_C	low risk	low A_{TBR}, right higher PF_α, low A_{MFN}, high A_{ERN} and low A_{P300}
Power	*HL*		medium social	medium A_{mu}, medium F_α
	LH	P_R	high risk	high A_{TBR}, right higher PF_α, high A_{MFN}, low A_{ERN} and high A_{P300}

play with Candy contributed to the study of the L-H component. According to the regression results, no player behaviour in the IPP explained H-L power, while the play with Ruby contributed to L-H power.

Overall, we evaluated risk-taking and social behaviour using the EEG recordings from play in the IPP. On the basis of the NPCs where player behaviour related to motive profiles, we first evaluated the EEG signals from selected NPCs to see if there was any significant impact on motive profile according to our proposed conceptual model. Later, we synthesised EEG signals to explore the effectiveness of each NPC to study mental states with motive profiles.

6.3.4 Results

To examine the difference between EEG features among different motive profiles, we used the independent t-test to determine the significance of the differences between EEG mental indicators for the H-L and L-H situations of each motivation. A t-test is a statistic that checks if two means (averages) are reliably different from each other, and independent t-test tests the means of two different groups. Only the H-L and L-H situations of achievement, affiliation and power motivation are evaluated pair-wise in this chapter. Differences are identified when the p-value of

	L-H Ach	L-H Aff	H-L Aff	H-L Ach	L-H Pow
L-H Ach	1.000	0.274	***0.019***	0.087	0.053
L-H Aff	0.274	1.000	0.112	0.103	0.151
H-L Aff	***0.019***	0.112	1.000	0.874	0.319
H-L Ach	0.087	0.103	0.874	1.000	0.485
L-H Pow	0.053	0.151	0.319	0.485	1.000

(a) Money feedback

	L-H Ach	H-L Aff	H-L Ach	L-H Aff	L-H Pow
L-H Ach	1.000	***0.025***	0.091	0.131	***0.028***
H-L Aff	***0.025***	1.000	0.647	0.569	***0.027***
H-L Ach	0.091	0.647	1.000	0.881	0.237
L-H Aff	0.131	0.569	0.881	1.000	0.441
L-H Pow	***0.028***	***0.027***	0.237	0.441	1.000

(b) Satisfaction feedback

Figure 6.1: Results of using ACC mu band in money and satisfaction feedback to reveal social attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

the t-test is less than 0.05 ($p < 0.05$).

We first determined the performance of using selected EEG features to predict social attitudes, when participants play with NPCs chosen from regression models. Fig. 6.1(a) and Fig. 6.2(a) show the performance of using EEG features to predict social attitude when players receive money feedback. Fig. 6.1(b) and Fig. 6.2(b) show the performance of using the same EEG features to predict social attitude when players receive satisfaction feedback. We found that social attitude is expressed more often by EEG signals collected during receipt of satisfaction feedback than those collected during receipt of money feedback. Furthermore, the ACC mu band and frontal alpha asymmetry performed almost equally to indicate social attitude.

We also explored the use of EEG features to predict risk-taking attitude when players receive money and satisfaction feedback. As shown in Fig. 6.3(a), Fig. 6.4(a) and Fig. 6.5(a), EEG features, ACC ERN, MFN and P300 from money feedback outperformed those features from satisfaction feedback that are shown in Fig 6.3(b), Fig. 6.4(b) and Fig. 6.5(b). Also, prefrontal alpha asymmetry can distinguish only two different types of motive situation for both money and satisfaction feedback (shown in Fig. 6.6(a) and Fig. 6.6(b)). In conclusion, the EEG features suggested by the literature all appear to have possibilities for predicting risk-taking attitude,

	H-L Ach	L-H Ach	H-L Aff	L-H Aff	L-H Pow
H-L Ach	1.000	0.320	0.055	0.391	0.088
L-H Ach	0.320	1.000	0.261	0.146	0.683
H-L Aff	0.055	0.261	1.000	0.056	0.490
L-H Aff	0.391	0.146	0.056	1.000	0.205
L-H Pow	0.088	0.683	0.490	0.205	1.000

(a) Money feedback

	L-H Aff	L-H Pow	L-H Ach	H-L Ach	H-L Aff
L-H Aff	1.000	0.266	0.088	0.158	***0.021***
L-H Pow	0.266	1.000	0.351	0.220	***0.027***
L-H Ach	0.088	0.351	1.000	0.812	0.149
H-L Ach	0.158	0.220	0.812	1.000	0.317
H-L Aff	***0.021***	***0.027***	0.149	0.317	1.000

(b) Satisfaction feedback

Figure 6.2: Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

	L-H Aff	H-L Ach	H-L Aff	L-H Ach	L-H Pow
L-H Aff	1.000	0.317	***0.039***	***0.010***	***0.009***
H-L Ach	0.317	1.000	0.120	***0.012***	***0.007***
H-L Aff	***0.039***	0.120	1.000	***0.031***	***0.015***
L-H Ach	***0.010***	***0.012***	***0.031***	1.000	0.693
L-H Pow	***0.009***	***0.007***	***0.015***	0.693	1.000

(a) Money feedback

	H-L Ach	L-H Ach	H-L Aff	L-H Aff	L-H Pow
H-L Ach	1.000	0.751	0.248	0.451	0.815
L-H Ach	0.751	1.000	0.401	0.674	0.619
H-L Aff	0.248	0.401	1.000	0.826	0.274
L-H Aff	0.451	0.674	0.826	1.000	0.529
L-H Pow	0.815	0.619	0.274	0.529	1.000

(b) Satisfaction feedback

Figure 6.3: Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

	L-H Ach	L-H Pow	H-L Aff	H-L Ach	L-H Aff
L-H Ach	1.000	0.567	***0.024***	***0.003***	***0.016***
L-H Pow	0.567	1.000	0.309	0.069	0.146
H-L Aff	***0.024***	0.309	1.000	***0.009***	0.065
H-L Ach	***0.003***	0.069	***0.009***	1.000	0.904
L-H Aff	***0.016***	0.146	0.065	0.904	1.000

(a) Money feedback

	H-L Ach	L-H Ach	H-L Aff	L-H Aff	L-H Pow
H-L Ach	1.000	0.665	0.475	0.133	0.309
L-H Ach	0.665	1.000	0.916	0.618	0.196
H-L Aff	0.475	0.916	1.000	0.561	0.096
L-H Aff	0.133	0.618	0.561	1.000	0.119
L-H Pow	0.309	0.196	0.096	0.119	1.000

(b) Satisfaction feedback

Figure 6.4: Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

	L-H Pow	L-H Ach	H-L Aff	H-L Ach	L-H Aff
L-H Pow	1.000	0.257	0.055	***0.034***	***0.034***
L-H Ach	0.257	1.000	0.101	***0.001***	***0.002***
H-L Aff	0.055	0.101	1.000	0.059	***0.021***
H-L Ach	***0.034***	***0.001***	0.059	1.000	0.287
L-H Aff	***0.034***	***0.002***	***0.021***	0.287	1.000

(a) Money feedback

	H-L Ach	L-H Ach	H-L Aff	L-H Aff	L-H Pow
H-L Ach	1.000	0.068	0.467	0.979	0.079
L-H Ach	0.068	1.000	0.506	0.058	0.203
H-L Aff	0.467	0.506	1.000	0.512	0.138
L-H Aff	0.979	0.058	0.512	1.000	0.110
L-H Pow	0.079	0.203	0.138	0.110	1.000

(b) Satisfaction feedback

Figure 6.5: Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

	L-H Pow	H-L Aff	L-H Ach	H-L Ach	L-H Aff
L-H Pow	1.000	0.652	0.222	***0.005***	0.271
H-L Aff	0.652	1.000	0.558	0.151	0.214
L-H Ach	0.222	0.558	1.000	0.258	0.311
H-L Ach	***0.005***	0.151	0.258	1.000	0.623
L-H Aff	0.271	0.214	0.311	0.623	1.000

(a) Money feedback

	H-L Aff	L-H Ach	H-L Ach	L-H Pow	L-H Aff
H-L Aff	1.000	0.380	0.390	0.228	***0.044***
L-H Ach	0.380	1.000	0.855	0.605	0.093
H-L Ach	0.390	0.855	1.000	0.795	0.218
L-H Pow	0.228	0.605	0.795	1.000	0.227
L-H Aff	***0.044***	0.093	0.218	0.227	1.000

(b) Satisfaction feedback

Figure 6.6: Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

	H-L Ach	L-H Ach	L-H Pow	H-L Aff	L-H Aff
H-L Ach	1.000	0.247	0.229	0.665	0.376
L-H Ach	0.247	1.000	0.778	0.108	0.731
L-H Pow	0.229	0.778	1.000	0.143	0.674
H-L Aff	0.665	0.108	0.143	1.000	0.210
L-H Aff	0.376	0.731	0.674	0.210	1.000

(a) Money feedback

	H-L Ach	L-H Ach	L-H Pow	H-L Aff	L-H Aff
H-L Ach	1.000	0.194	0.145	0.361	0.719
L-H Ach	0.194	1.000	0.221	0.136	0.225
L-H Pow	0.145	0.221	1.000	0.455	0.159
H-L Aff	0.361	0.136	0.455	1.000	0.364
L-H Aff	0.719	0.225	0.159	0.364	1.000

(b) Satisfaction feedback

Figure 6.7: Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components of each motivation is presented. Grey squares indicate significant differences.

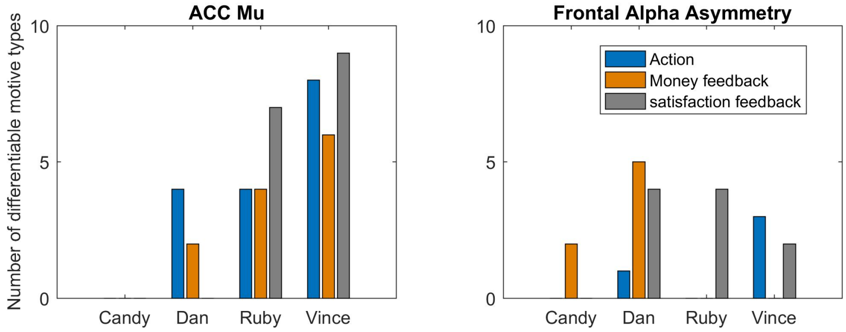


Figure 6.8: Performance of EEG and NPC features for predicting social attitude.

except for ACC TBR (see Fig. 6.7(a) and Fig. 6.7(b)).

Next, we assessed EEG features from the IPP to see how they reveal risk-taking and social attitudes. This section displays a summary of experimental results. Detailed numerical results are shown in Appendix D. First, we used EEG features to predict social attitude in the IPP from different perspectives. Fig. 6.8 summarises the performance of predicting social attitude from EEG data collected when players act against each NPC. The results show that the EEG features collected during action against Candy had no ability to differentiate player motive profiles, while data collected during interaction with Vince was more useful for this work.

By analysing social attitude using EEG features collected during interaction with each NPC, we summarise the performance of using NPCs to reveal social attitudes in Fig. 6.9. Data collected during action against and satisfaction feedback from Candy performed worse than data collected during those interactions with the other three characters. Data collected during action against and satisfaction feedback from Vince had better performance that those data collected from other characters. Data collected during satisfaction feedback from Ruby had better performance and data collected during money feedback from Dan had slightly better performance. Overall, the results indicate that Ruby and Vince are good choices for evoking social attitudes, while Candy is not appropriate for achieving this goal.

We also evaluated the use of each NPC to predict risk-taking attitudes using EEG features when players make actions, receive money and satisfaction feedback. Fig. 6.10 shows that data collected during actions against Candy and Ruby per-

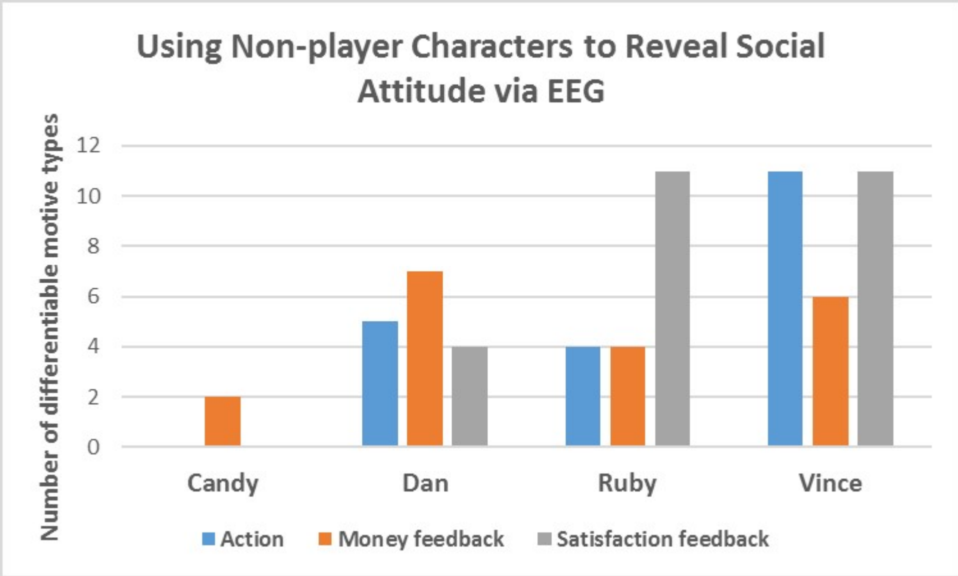


Figure 6.9: Using NPCs to reveal social attitude via EEG analysis

formed the poorest at predicting risk-taking attitude. Whereas, data collected during actions against Dan and Vince suggest they performed better than the other characters at predict risk-taking attitude.

Fig. 6.10 summarises the performance of each NPC to predict risk-taking attitude when players receive satisfaction feedback. It shows that data collected during satisfaction feedback from Ruby was the best predictor of risk-taking attitude, and data collected during satisfaction feedback from Vince was the worst predictor of risk-taking attitude.

As shown in Fig. 6.11, EEG signals collected during action, money and satisfaction feedback from Candy do not allow us to significantly differentiate the player motive profile. When data was collected during action against Dan and Vince gave the best performance, whereas data was collected during money feedback from Dan gave the best performance and then data was collected during satisfaction feedback from Ruby gave the best performance. Overall, Candy is also the least useful character for revealing risk-taking attitudes, while Dan, Ruby and Vince are appropriate choices for evoking risk-taking attitudes when players make actions, receive money and satisfaction feedback.

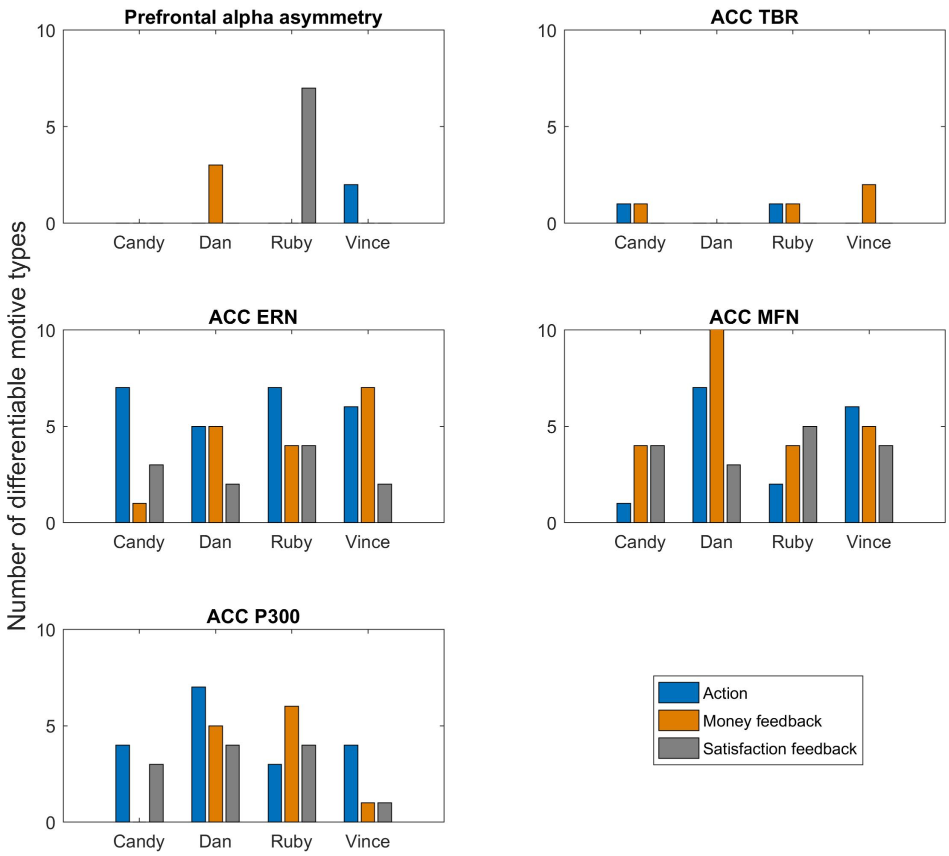


Figure 6.10: Performance of EEG and NPC features for predicting risk attitude.

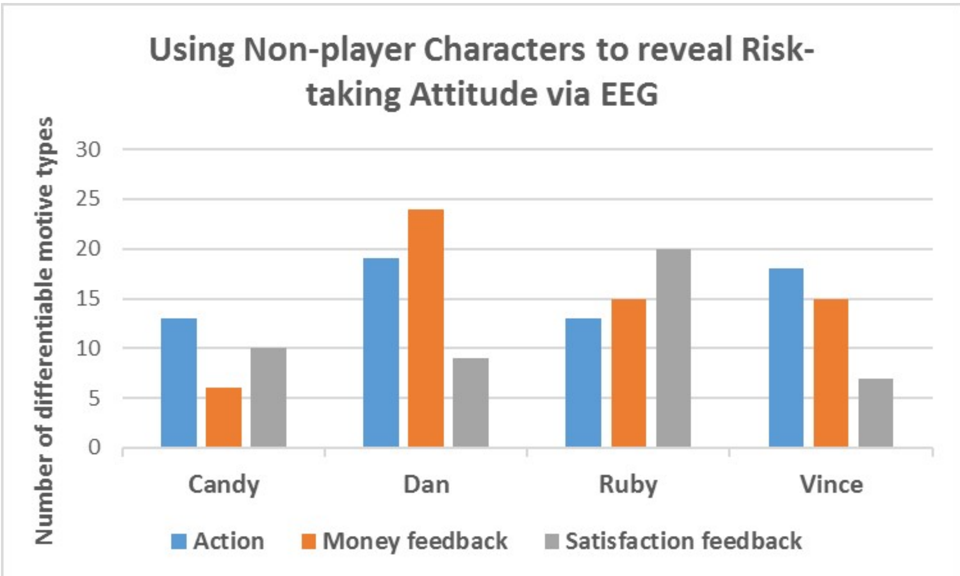


Figure 6.11: Using NPCs to reveal risk-taking attitude via EEG analysis

6.3.5 Discussion

EEG analysis in the IPP demonstrates that EEG signals collected during satisfaction feedback indicate social attitude, while EEG signals collected during money feedback appear to reveal risk-taking attitude. The results demonstrate the effectiveness of the NPCs, two dimensions of money and satisfaction, at reflecting players' risk-taking and social attitudes.

In addition, we hypothesised that depending on their design, different NPCs would reveal the risk-taking and social attitudes of different motivated players. After analysing the effectiveness of using each NPC in the IPP for revealing risk-taking and social attitudes, we found using EEG signals that Candy is the least useful character for learning human risk-taking and social attitudes. Ruby and Vince are found to be a good choice for evoking social attitude, while Dan, Ruby and Vince are found to be useful for evoking risk-taking attitudes.

Candy emerged as the weakest NPC for assessing risk attitude. This could be because players cannot be defected against by Candy, regardless of their actions. Candy always cooperates which gives an impression of no risk during the interaction. Moreover, Candy does not appear to evoke social attitude, probably because Candy cannot be satisfied even if players cooperate with her (see Fig. 3.7). This means that players are reluctant to pursue friendships with Candy. In future alternative play strategies should be investigated to reveal more about players.

Results reported in Fig.6.8 shows that ACC mu band extracted from play with Vince have better performance than ACC mu band extracted from play with other characters. The ACC region is the significant brain region for monitoring working memory [157]. Thus, it seems that players need to memorize the last action of Vengeful Vince in order to play with him. In contrast, playing with Random Ruby requires less working memory because the actions of this character are random. Furthermore, for Defector Dan and Cooperator Candy, players use less working memory because their actions are consistent and completely predictable.

6.4 Analysing Individual Play and Social Network Phases for Assessing Motivation

For a better understanding of the mini-game that allows for differentiating between motive profiles, we further examined EEG signals from the SNP. Recall that the IPP is one versus one play, while the SNP is one versus many play. We compared the performance of EEG features from the SNP with other findings in the previous section, to assess the effectiveness of the IPP versus SNP for player motive profiling. A t-test was applied to examine the significance of differences between EEG features in the SNP with the H-L and L-H situation of each motivation. Results showed that the EEG signals collected from the SNP can be used as an indicator for identifying player motivation, but the performance is worse than the performance of using EEG signals collected from the IPP. It suggests that the design of SNP requires several improvements in future studies.

6.4.1 Aim

The aim of this experiment is to compare the performance of the IPP and SNP in assessing player motivation. Firstly, we analyse the use of the SNP for identifying mental indicators of player motive profiles. Then we compare the performance of the IPP and SNP by summarising some aforementioned findings.

6.4.2 Hypothesis

We hypothesise that both the IPP and the SNP can be used for identifying risk-taking and social attitudes of different player motive profiles.

6.4.3 Method

The same EEG signal processing approach was employed as in Section 6.3.2. Corresponding EEG features were extracted for risk-taking and social attitudes (as shown in Tab. 6.5). To identify feature differences between motive profiles, an independent t-test was applied and the threshold for statistical significance is that the p-value is less than 0.05 ($P < 0.05$). However, as there is no latency time for money feedback and satisfaction feedback in the SNP (too many stimuli in the interface), we focused our EEG signal analysis during participant actions (time from 0s to 500ms) and each trial. This is a preliminary study to explore the possibility of using social network play to evoke risk-taking and social attitudes.

6.4.4 Results

In the SNP, we first assessed the performance of using EEG features to distinguish differences in social attitudes between the H-L and L-H situations of each motivation. Fig. 6.12(a) and Fig. 6.13(a) indicate that EEG signals from the SNP have the potential to reveal social attitude. In particular, we focus on the time interval when players make their actions as shown in Fig. 6.12(b), Fig. 6.13(b). This illustrates that players with different motive profiles expressed different social attitudes when they played against their social network.

We also examined the EEG features from the SNP for assessing risk-taking attitudes. Fig. 6.14(a), Fig. 6.15(a), Fig. 6.16(a) and Fig. 6.17(a) show that the design of SNP has the potential to evoke risk-taking attitudes via EEG signals. However, the ACC TBR feature (see in 6.7(a) and 6.7(b)) was unable to differentiate between the H-L and L-H situations of any motive. By examining players' actions in the SNP, we can see from Fig. 6.14(b), Fig. 6.15(b), Fig. 6.16(b) and Fig. 6.17(b) that players with different motive types had various risk-taking attitudes when playing against their social network.

	L-H Ach	H-L Pow	L-H Pow	L-H Aff	H-L Aff	H-L Ach
L-H Ach	1.000	0.510	0.196	0.194	0.154	***0.001***
H-L Pow	0.510	1.000	0.544	0.528	0.321	***0.001***
L-H Pow	0.196	0.544	1.000	0.884	0.764	***0.018***
L-H Aff	0.194	0.528	0.884	1.000	0.841	***0.037***
H-L Aff	0.154	0.321	0.764	0.841	1.000	***0.049***
H-L Ach	***0.001***	***0.001***	***0.018***	***0.037***	***0.049***	1.000

(a) SNP

	L-H Ach	H-L Pow	L-H Aff	L-H Pow	H-L Aff	H-L Ach
L-H Ach	1.000	0.336	0.340	0.193	0.066	***0.003***
H-L Pow	0.336	1.000	0.912	0.691	0.182	***0.004***
L-H Aff	0.340	0.912	1.000	0.664	0.425	0.056
L-H Pow	0.193	0.691	0.664	1.000	0.475	***0.045***
H-L Aff	0.066	0.182	0.425	0.475	1.000	0.141
H-L Ach	***0.003***	***0.004***	0.056	***0.045***	0.141	1.000

(b) Action

Figure 6.12: Results of using ACC mu band in the whole SNP and during action to reveal social attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	L-H Aff	H-L Ach	L-H Ach	H-L Pow	H-L Aff	L-H Pow
L-H Aff	1.000	0.367	***0.000***	***0.000***	***0.000***	***0.000***
H-L Ach	0.367	1.000	***0.034***	***0.006***	***0.002***	***0.026***
L-H Ach	***0.000***	***0.034***	1.000	0.698	0.316	0.429
H-L Pow	***0.000***	***0.006***	0.698	1.000	0.529	0.600
H-L Aff	***0.000***	***0.002***	0.316	0.529	1.000	0.928
L-H Pow	***0.000***	***0.026***	0.429	0.600	0.928	1.000

(a) SNP

	L-H Aff	H-L Ach	L-H Pow	L-H Ach	H-L Aff	H-L Pow
L-H Aff	1.000	0.362	***0.010***	***0.011***	***0.000***	***0.000***
H-L Ach	0.362	1.000	0.672	0.452	0.096	0.063
L-H Pow	***0.010***	0.672	1.000	0.624	***0.017***	***0.047***
L-H Ach	***0.011***	0.452	0.624	1.000	0.150	0.105
H-L Aff	***0.000***	0.096	***0.017***	0.150	1.000	0.691
H-L Pow	***0.000***	0.063	***0.047***	0.105	0.691	1.000

(b) Action

Figure 6.13: Results of using frontal alpha asymmetry in the whole SNP and during action to reveal social attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	L-H Pow	H-L Aff	H-L Pow	L-H Ach	H-L Ach	L-H Aff
L-H Pow	1.000	0.353	0.691	0.834	0.189	***0.001***
H-L Aff	0.353	1.000	0.648	0.478	0.326	***0.000***
H-L Pow	0.691	0.648	1.000	0.826	0.298	***0.002***
L-H Ach	0.834	0.478	0.826	1.000	0.225	***0.001***
H-L Ach	0.189	0.326	0.298	0.225	1.000	***0.022***
L-H Aff	***0.001***	***0.000***	***0.002***	***0.001***	***0.022***	1.000

(a) SNP

	H-L Pow	H-L Aff	L-H Ach	H-L Ach	L-H Pow	L-H Aff
H-L Pow	1.000	0.373	0.368	0.296	0.133	***0.029***
H-L Aff	0.373	1.000	0.861	0.511	0.110	***0.012***
L-H Ach	0.368	0.861	1.000	0.717	0.356	0.071
H-L Ach	0.296	0.511	0.717	1.000	0.574	0.152
L-H Pow	0.133	0.110	0.356	0.574	1.000	0.170
L-H Aff	***0.029***	***0.012***	0.071	0.152	0.170	1.000

(b) Action

Figure 6.14: Results of using prefrontal alpha asymmetry in the whole SNP and during action to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	L-H Aff	H-L Pow	L-H Ach	L-H Pow	H-L Aff	H-L Ach
L-H Aff	1.000	0.692	0.430	***0.042***	***0.032***	0.280
H-L Pow	0.692	1.000	0.347	0.221	0.088	0.424
L-H Ach	0.430	0.347	1.000	0.117	0.222	0.086
L-H Pow	***0.042***	0.221	0.117	1.000	0.200	0.117
H-L Aff	***0.032***	0.088	0.222	0.200	1.000	***0.010***
H-L Ach	0.280	0.424	0.086	0.117	***0.010***	1.000

(a) SNP

	H-L Pow	L-H Ach	L-H Aff	L-H Pow	H-L Aff	H-L Ach
H-L Pow	1.000	0.119	0.505	0.417	***0.025***	0.266
L-H Ach	0.119	1.000	0.485	0.710	0.640	***0.016***
L-H Aff	0.505	0.485	1.000	0.823	0.232	0.153
L-H Pow	0.417	0.710	0.823	1.000	0.431	0.148
H-L Aff	***0.025***	0.640	0.232	0.431	1.000	***0.001***
H-L Ach	0.266	***0.016***	0.153	0.148	***0.001***	1.000

(b) Action

Figure 6.15: Results of using ACC ERN in the whole SNP and during action to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	H-L Ach	L-H Pow	H-L Aff	L-H Ach	L-H Aff	H-L Pow
H-L Ach	1.000	0.100	***0.001***	***0.042***	0.712	0.328
L-H Pow	0.100	1.000	0.300	0.509	***0.023***	0.274
H-L Aff	***0.001***	0.300	1.000	***0.022***	***0.000***	***0.005***
L-H Ach	***0.042***	0.509	***0.022***	1.000	***0.014***	0.272
L-H Aff	0.712	***0.023***	***0.000***	***0.014***	1.000	0.471
H-L Pow	0.328	0.274	***0.005***	0.272	0.471	1.000

(a) SNP

	H-L Ach	L-H Pow	H-L Aff	L-H Aff	L-H Ach	H-L Pow
H-L Ach	1.000	0.129	***0.005***	0.851	***0.024***	0.319
L-H Pow	0.129	1.000	0.739	0.090	0.990	0.325
H-L Aff	***0.005***	0.739	1.000	***0.003***	0.640	***0.042***
L-H Aff	0.851	0.090	***0.003***	1.000	***0.013***	0.383
L-H Ach	***0.024***	0.990	0.640	***0.013***	1.000	0.141
H-L Pow	0.319	0.325	***0.042***	0.383	0.141	1.000

(b) Action

Figure 6.16: Results of using ACC MFN in the whole SNP and during action to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	H-L Ach	L-H Ach	H-L Pow	L-H Pow	H-L Aff	L-H Aff
H-L Ach	1.000	0.215	0.325	0.523	***0.001***	0.607
L-H Ach	0.215	1.000	0.908	0.554	***0.000***	***0.002***
H-L Pow	0.325	0.908	1.000	0.744	***0.007***	0.077
L-H Pow	0.523	0.554	0.744	1.000	***0.002***	***0.033***
H-L Aff	***0.001***	***0.000***	***0.007***	***0.002***	1.000	***0.000***
L-H Aff	0.607	***0.002***	0.077	***0.033***	***0.000***	1.000

(a) SNP

	L-H Pow	L-H Ach	L-H Aff	H-L Ach	H-L Aff	H-L Pow
L-H Pow	1.000	0.679	0.100	0.554	0.073	0.321
L-H Ach	0.679	1.000	0.095	0.264	***0.004***	0.078
L-H Aff	0.100	0.095	1.000	0.078	***0.000***	***0.011***
H-L Ach	0.554	0.264	0.078	1.000	0.447	0.846
H-L Aff	0.073	***0.004***	***0.000***	0.447	1.000	0.478
H-L Pow	0.321	0.078	***0.011***	0.846	0.478	1.000

(b) Action

Figure 6.17: Results of using ACC P300 in the whole SNP and during action to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

	H-L Ach	L-H Ach	H-L Pow	L-H Pow	H-L Aff	L-H Aff
H-L Ach	1.000	0.533	0.280	0.561	0.479	0.928
L-H Ach	0.533	1.000	0.853	0.317	0.887	0.492
H-L Pow	0.280	0.853	1.000	0.159	0.669	0.244
L-H Pow	0.561	0.317	0.159	1.000	0.218	0.598
H-L Aff	0.479	0.887	0.669	0.218	1.000	0.427
L-H Aff	0.928	0.492	0.244	0.598	0.427	1.000

(a) SNP

	L-H Aff	L-H Pow	H-L Pow	H-L Ach	H-L Aff	L-H Ach
L-H Aff	1.000	0.773	0.843	0.212	*0.019*	*0.014*
L-H Pow	0.773	1.000	0.926	0.426	0.056	*0.036*
H-L Pow	0.843	0.926	1.000	0.835	0.474	0.400
H-L Ach	0.212	0.426	0.835	1.000	0.208	0.110
H-L Aff	*0.019*	0.056	0.474	0.208	1.000	0.549
L-H Ach	*0.014*	*0.036*	0.400	0.110	0.549	1.000

(b) Action

Figure 6.18: Results of using ACC TBR in the whole SNP and during action to reveal risk-taking attitude. The p-value of independent t-test between hope and fear components for each motivation is presented. Grey squares indicate significant differences.

6.4.5 Discussion

The results indicate that EEG signals collected from the SNP can be used as an indicator for identifying player motivation, which supports our hypothesis. Furthermore, we compare the performances between the IPP and SNP with previous findings. As discussed in Section 5.3.3, EEG signals from the IPP slightly outperformed EEG signals from the SNP for classifying hope for control and fear of loss of control. Also, EEG signals from the SNP had the poorest performance for classifying affiliation motivation compared to the performance of EEG signals from the IPP. Moreover, we found in Section 6.3 that players' attitudes towards risk-taking can be revealed with the use of the money feature, while players' social attitude can be learned from the satisfaction feature. Because of the absence of latency of money and satisfaction feedback in the SNP, there was not enough information to distinguish aspects of achievement, affiliation and power motivation. In future studies, the design of money and satisfaction feedback in the SNP needs to be considered.

There are several reasons why the performance of the SNP is not ideal. First, we can only examine the action and trials in the SNP because there is no latency for money and satisfaction feedback. Feedback-related potentials are essential for assessing risk-taking and social attitudes, which are two characteristics of player motivation [49,50,121]. Future work needs to consider how to design the money and satisfaction feedback stimuli in the SNP to avoid too many stimuli in the interface. In addition, the design of the SNP for evoking social attitude is solid, however, the use of the SNP for risk attitude need to be enhanced in the future study. Using Ruby, the random character as the uncertain and risky element in the SNP emerged as inadequate. Finally, the gameplay between players and NPCs are in a pairwise fashion. Further works should consider alternative game mechanics of the social network play, for instance, the n-player iterated prisoner dilemma.

6.5 Conclusion

This chapter validates the design of our mini-game using player behaviour and EEG signals. Results show that motivation profiles can be modelled by the player behaviour with each NPC in two phases of the mini-game. More importantly, social attitude can be revealed by EEG signals collected during satisfaction feedback, and risk-taking attitude can be evoked in EEG signals collected during money feedback. To be more specific, Ruby and Vince are good choices for evoking social attitude; Dan, Ruby and Vince are good choices for evoking risk-taking attitudes. However, Candy is the least useful character for reflecting social and risk-taking attitudes. It also appears that player behaviour and EEG data collected from the IPP allow us to assess motivation better than those from the SNP.

In the next chapter, we will focus on using EEG signals to explore the relevant EEG features and brain regions for revealing player motivation.

Chapter 7

Identifying Electroencephalographic Features for Player Motive Profiling

7.1 Introduction

As we examined in Chapter 5, EEG technology can be a promising indicator for classifying player motivation when players engage in a game. In Chapter 6, more specific investigations were performed to seek insights into why player behaviour and EEG signals can be used to classify motivation. We examined the use of different parts of our mini-game for distinguishing different aspects of motivation. According to the literature review in Chapter 2, we selected several EEG features discussed in the existing literature to propose a conceptual model that links motivation theory to EEG technology. Chapter 6 examined the performance of these selected EEG features for differentiating risk-taking and social attitudes across different player motive profiles. This chapter takes two approaches to identifying EEG features that are the best indicators of achievement, affiliation and power motivation. The first approach was to investigate the relationships between EEG features from the existing literature and player motivation profile. After that, a machine learning based approach was employed to explore the possible additional EEG features that can identify player motivation. We conclude by combining our findings to associate relevant EEG features with the corresponding brain regions, thereby allowing us to assess player motivation when using EEG signals from different phases of our mini-game.

In this chapter, we examine the EEG features identified in the existing literature that we hypothesise could be used to assess player motivation in Section 7.2. Section 7.3 analyses the EEG signals from our mini-game to extract a wide range of features using a machine learning technique. Temporal, spectral, time-frequency and asymmetry features are extracted from the signals. The details of the EEG features, including different channels, feature type and brain regions, are also elaborated in Section 7.3. We summarise our conclusions in Section 7.4.

7.2 Identifying EEG Features for Assessing Player Motivation from Literature

Based on the literature review in Chapter 2, we identified the possibilities for using EEG features to identify risk attitude, social attitude and emotion, which are three key aspects of achievement, affiliation and power motivation. Several EEG features are summarized from the EEG studies of risk-taking, social attitude and emotion and are regarded as possible indicators for assessing player motivation. In this section, we examine the use of EEG features mentioned in the existing literature for assessing player motivation. Correlation analysis was employed to examine the relationships between EEG features from the different parts of the game and motivation variables. Results showed that across different part of the game, frontal alpha asymmetry, prefrontal alpha asymmetry, ACC TBR, ACC MFN and parietal beta are related to player motive profiles. The results validate the proposed conceptual model and identify the possible EEG indicators for profiling player motivation.

7.2.1 Aim

The aim of this experiment is to validate each link in a proposed conceptual model for using EEG features to identify player motive profiles. We examine our conceptual model (see Fig. 7.2) using EEG signals from different parts of our mini-game. This will demonstrate whether the proposed EEG features in our conceptual model have the potential to identify player motivation through EEG signals in the mini-game.

7.2.2 Hypothesis

Based on the three characteristics of achievement, affiliation and power motivation in psychological theory, we further reviewed EEG papers about emotion, risk-taking and social attitudes. Emotion recognition using EEG signals has been studied widely in terms of experimental scenarios, EEG features, brain regions and data analysis. For instance, frontal alpha asymmetry is understood to be an EEG indicator for emotion, with greater left frontal alpha being associated with positive emotion and approach motivation, while greater right frontal alpha is associated with negative emotion and withdrawal motivation [113]. Research has also revealed that the beta band in the parietal region reflects emotional processes [34]. The gamma band in the temporal region is an important indicator for emotion recognition, as has been suggested by several studies [41, 86].

Recognition of risk-taking and social attitude have been explored in EEG studies. Pre-frontal alpha asymmetry (greater right than left) was found to be associated with riskier strategies [119]. Another spectral feature, the theta-beta ratio is relevant to feedback-related negativity with increased risk-taking behaviour [48]. Various kinds of event-related potentials (ERPs) have been proposed to be associated with risk-taking behaviour. For example, low risk-taking behaviour is associated with an increase in the feedback event-related negativity (ERN) amplitude in the anterior cingulate cortex (ACC) region [49]. Studies also indicate that medial frontal negativity (MFN) increases after the feedback signals with larger gains onset [121].

Table 7.1: Features extracted for identifying mental indicators (risk-taking, social and emotion) of motive profile

Category	*Feature*	*Brain region*	*Mental state*
Temporal	ERN	ACC	Risk
	MFN	ACC	Risk
	P300	ACC	Risk
Time-frequency	Mu band	ACC	Social
	Beta band	Parietal	Emotion
	Gamma band	Temporal	Emotion
	Theta-beta ratio	ACC	Risk
Asymmetry	alpha band	Frontal	Social and emotion
	alpha band	Pre-frontal	Risk

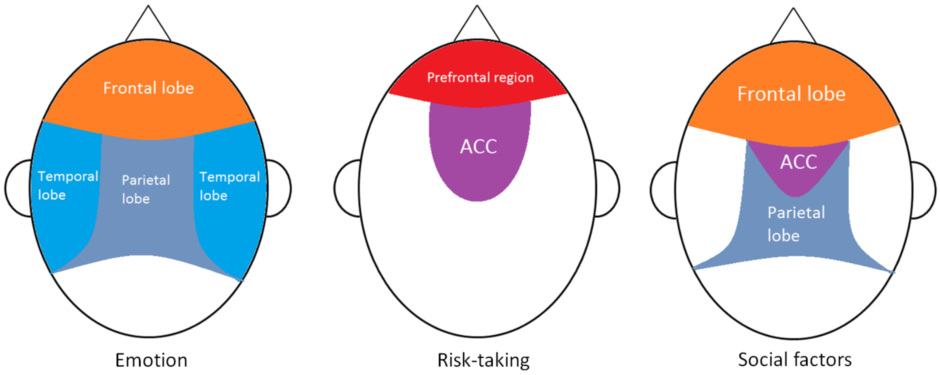
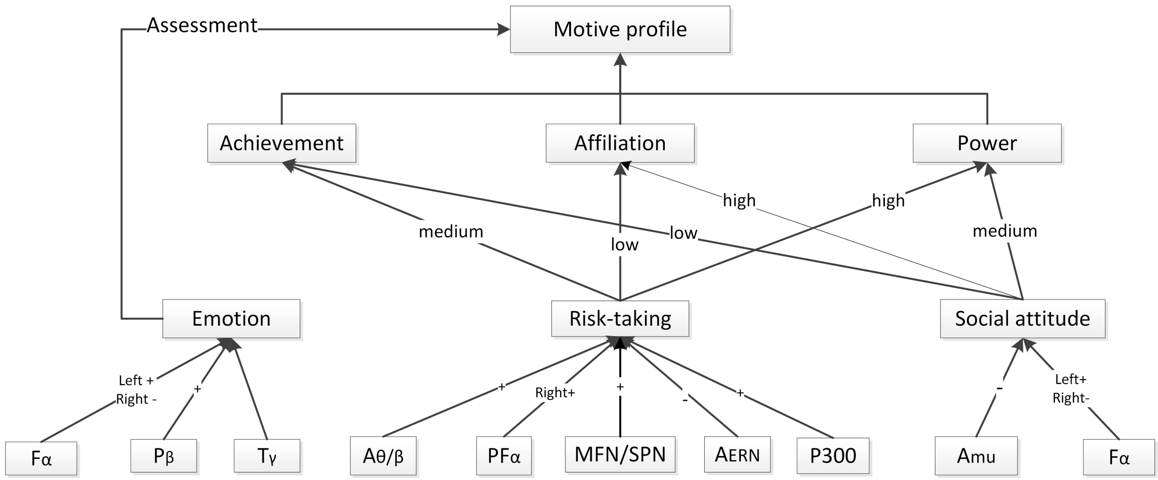


Figure 7.1: The brain regions associated with emotion, risk-taking behaviour and social factors

P300 is also related to high risk-taking behaviour [50]. Two EEG features, mu band in the ACC and frontal alpha asymmetry, have been revealed to be useful for revealing social behaviour. Perry et al. demonstrated that the mu band in the ACC increases when experiencing opponent actions in a social game [51, 134]. Frontal alpha asymmetry is reported to influence antisocial behaviour [133].

We summarised and illustrated the related brain regions for emotion, risk-taking behaviour and social factors. Fig. 7.1 shows clearly that the frontal lobe, especially the prefrontal region, is the brain region activated for emotion, risk-taking and social factors. In addition, the ACC plays a significant role in these three factors. We can also see from Tab. 7.1 that the alpha band (8-12Hz) or mu rhythm could be used to represent emotion, risk-taking and social factors.

Fig. 7.2 summarises our discussion of EEG signal processing for risk-taking, emo-



F = frontal region P = parietal region T = temporal region A = anterior cingulate cortex PF = pre-frontal lobe

α = alpha band β = beta band γ = gamma band θ/β =theta-beta-ratio mu = mu band MFN = medial frontal negativity SPN = stimulus-preceding negativity ERN = error-related negativity ERPs = event-related potentials

Figure 7.2: A synthesised tree of EEG signal processing for motivation types

tion and social attitude, and its link to achievement, affiliation and power motivation. The top part of Fig. 7.2 shows how motivation types are influenced by risk-taking and social attitudes. The bottom part of Fig. 7.2 shows the influence of different features (the second lower level) and EEG channels (the bottom level) on emotion, risk-taking and social characteristics (the EEG channels are consistent with a 10-20 system). The left-most branch of Fig. 7.2 linking emotion to motive profile represents a path for assessing the link between risk-taking and social attitude and achievement, affiliation and power motivation, Hence, we hypothesise that a person with a particular motive profile should show aspects of emotion, described in Tab. 2.2 Chapter 2, when engaged in combinations of risk-taking or social activities linked to those motives outlined in Fig. 7.2.

In other words, depending on the different levels of challenge in the game, individuals with achievement, affiliation and power motivations may present different risk-taking behaviour, and then experience different flow zones, which ultimately helps to assess the classification of player motivation types.

7.2.3 Method

We examined our proposed conceptual model in three parts of the game. Firstly, we used EEG signals from two phases of our mini-game, the IPP and SNP (the same EEG signals used in Chapter 5 for classifying player motivation). As presented in Chapter 6, EEG features from the IPP and SNP have the potential to differentiate risk-taking and social attitudes of player motive profiles. Thus, we further validate the possibilities of these EEG features for identifying player motivation. In addition, as discussed in Section 6.3, the money dimension of NPCs is a promising feature for understanding players' risk-taking attitudes, while the satisfaction dimension of NPCs has the potential to reveal players' social attitudes. Therefore, we selected EEG signals collected during participant interaction with a subset of NPCs (in Tab. 6.5). The subset of NPCs was also selected using the regression analysis of player behaviour and motivation variables in Chapter 6. In Section 6.3, we identified that money and satisfaction feedback of this subset of data can reveal social and risk-taking attitudes. Therefore, we further validated the EEG features in our conceptual model using the EEG signals from this subset of NPCs. Correlation analysis was used in this experiment to find relationships between EEG features and motivation variables from MMG test output.

7.2.4 Results

The correlation coefficients between motivation variables and EEG features from the IPP are listed in Tab. 7.2. The coefficients that are larger than 0.3 ($|r| > 0.3$) are highlighted in bold. $*$ means that the relationship between two variables are statistical significant ($P < 0.05$). In the IPP, we observed that several electrodes in frontal alpha asymmetry, prefrontal alpha asymmetry, ACC TBR, ACC MFN, ACC P300 and parietal beta were related to motivation variables. In particular, frontal alpha asymmetry had five related electrodes, while prefrontal alpha asymmetry, ACC TBR, ACC MFN, ACC P300 and parietal beta only had one related electrode. The ACC mu band, ACC ERN and temporal gamma showed no rela-

Table 7.2: Correlation coefficients between motivation variables and EEG features from the individual play phase

Features	***Electrodes***	***HE***	***FM***	***HA***	***FZ***	***HK***	***FK***
ACC mu	CPz	0.23	-0.13	0.13	-0.16	0.19	0.24
	FCz	0.20	-0.11	0.18	-0.18	0.20	0.24
	Cz	0.20	-0.09	0.19	-0.12	0.21	0.22
Frontal alpha asymmetry	FP1-FP2	0.14	0.03	0.03	0.07	0.14	0.13
	AFP5-AFP6	0.21	0.10	0.01	**0.44** ∗	**0.33**	**0.39**
	AF7-AF8	-0.02	-0.09	-0.27	0.22	-0.15	0.08
	AF5-AF6	0.00	**-0.31**	-0.07	-0.16	0.04	0.28
	AF3-AF4	-0.18	0.04	-0.24	0.29	-0.19	0.15
	AF1-AF2	-0.25	-0.02	0.21	0.01	-0.01	-0.29
	F7-F8	0.15	-0.21	-0.01	-0.08	-0.06	0.13
	F5-F6	-0.07	0.25	**-0.41**	**0.31**	0.05	**0.44** ∗
	F3-F4	-0.09	**0.44** ∗	**-0.48** ∗	0.20	-0.10	**0.43** ∗
	F1-F2	**-0.30**	-0.06	0.15	0.07	-0.03	-0.07
Prefrontal alpha asymmetry	FP1-FP2	0.14	0.03	0.03	0.07	0.14	0.13
	AFP5-AFP6	0.21	0.10	0.01	**0.44** ∗	**0.33**	**0.39**
	AF7-AF8	-0.02	-0.09	-0.27	0.22	-0.15	0.08
	AF5-AF6	0.00	**-0.31**	-0.07	-0.16	0.04	0.28
	AF3-AF4	-0.18	0.04	-0.24	0.29	-0.19	0.15
	AF1-AF2	-0.25	-0.02	0.21	0.01	-0.01	-0.29
ACC TBR	CPz	0.16	0.06	-0.13	0.23	**-0.44** ∗	-0.01
	FCz	-0.23	-0.15	-0.10	-0.18	**-0.33**	**-0.32**
	Cz	0.13	0.14	-0.01	0.17	-0.18	-0.24
ACC ERN (Money)	CPz	-0.20	0.23	-0.18	-0.04	-0.20	0.14
	FCz	-0.08	0.21	-0.22	0.22	0.08	-0.08
	Cz	-0.18	0.20	-0.24	-0.08	-0.14	0.06
ACC ERN (Satisfaction)	CPz	**0.32**	0.21	0.21	0.02	0.15	0.16
	FCz	0.25	0.08	**-0.34**	-0.16	0.08	0.16
	Cz	0.24	0.16	0.10	-0.05	0.22	0.04
ACC MFN (Money)	CPz	-0.29	0.12	-0.27	-0.24	-0.25	-0.08
	FCz	-0.11	0.21	-0.25	-0.03	-0.02	-0.12
	Cz	**-0.32**	0.03	**-0.38**	-0.28	**-0.32**	-0.08
ACC MFN (Satisfaction)	CPz	0.17	0.28	**0.38**	0.21	0.09	0.26
	FCz	0.23	**0.45** ∗	-0.17	0.25	0.19	**0.37**
	Cz	0.19	**0.33**	0.21	0.15	0.19	0.22
ACC P300 (Money)	CPz	-0.13	**0.30**	-0.06	-0.29	-0.04	0.22
	FCz	0.05	**0.36**	-0.21	0.01	**0.34**	0.09
	Cz	-0.25	0.17	**-0.33**	**-0.31**	-0.12	0.12
ACC P300 (Satisfaction)	CPz	-0.10	0.23	0.00	-0.16	-0.18	0.13
	FCz	-0.13	**0.59** ∗	**-0.39**	**0.30**	-0.14	0.27
	Cz	-0.08	0.25	0.07	-0.15	-0.10	-0.02
Parietal beta	PO7	0.05	-0.22	-0.06	-0.21	**-0.41**	0.01
	PO5	0.04	-0.26	0.02	-0.20	**-0.38**	0.03
	PO3	0.13	-0.26	0.16	**-0.32**	0.02	0.10
	PO1	0.09	-0.30	0.16	**-0.35**	-0.05	0.02
	Poz	0.02	-0.22	0.15	-0.26	-0.02	0.09
	PO2	-0.28	-0.07	0.10	0.05	**-0.33**	0.06
	PO4	-0.24	0.00	0.09	0.10	**-0.32**	0.21
	PO6	-0.11	0.18	-0.01	0.21	-0.26	**0.45** ∗
	PO8	0.13	-0.19	0.15	-0.23	0.08	0.12
Temporal gamma	FT7	0.15	-0.20	0.14	-0.23	0.04	0.17
	T7	0.14	-0.20	0.12	-0.26	0.04	0.17
	TP7	0.13	-0.26	0.08	-0.29	-0.01	0.10
	FT8	0.15	-0.15	0.15	-0.19	0.09	0.13
	T8	0.18	-0.14	0.14	-0.20	0.08	0.15
	TP8	0.20	0.00	0.03	0.06	-0.02	**0.34**

tionship with motivation variables. More specifically, as shown in Tab. 7.2, frontal alpha asymmetry had a negative relationship with hope for social acceptance, but positive relationships with fear of failure, fear of rejection and fear of loss of control. Prefrontal alpha asymmetry had a positive relationship with fear of rejection. ACC TBR had a negative relationship with hope for control. Moreover, ACC MFN collected during satisfaction feedback had a positive relationship with fear of failure. ACC P300 collected during satisfaction feedback had a positive relationship with fear of failure. Parietal beta had a positive relationship with fear of loss of control.

In the SNP, we can see from Tab. 7.3 that several electrodes from frontal alpha asymmetry, prefrontal alpha asymmetry, parietal beta had relationships with motivation variables. Temporal gamma had no relationship with motivation variables. The ACC mu band and ACC TBR only had one related electrodes. Specifically, frontal alpha asymmetry had a negative relationship with hope for social acceptance, and positive relationships with fear of rejection and hope of control. Prefrontal alpha asymmetry had a negative relationship with hope for social acceptance, and a positive relationship with hope for control. ACC TBR had a negative relationsihp with hope for control. Parietal beta had negative relationships with hope for control and fear of loss of control. Because there is no latency of money and satisfaction feedback in the SNP, no ACC ERN, MFN and P300 were extracted from EEG signals.

Tab. 7.4 lists correlation coefficients between motivation variables and EEG features from a subset of NPCs identified by the regression analysis. Electrodes from frontal alpha asymmetry, prefrontal alpha asymmetry, ACC TBR, ACC MFN and temporal gamma were found to have various relationships with motivation variables. However, ACC mu band, ACC ERN, ACC P300 and parietal beta had no related electrodes. ACC TBR and ACC MFN from money feedback had only one related electrode. Particularly, frontal alpha asymmetry had a positive relationship with fear of loss of control and a negative relationship with hope for social acceptance. Prefrontal alpha asymmetry had a positive relationship with fear of loss of control. ACC TBR had a negative relationship with hope for control. ACC MFN collected

Table 7.3: Correlation coefficients between motivation variables and EEG features from the social network phase

Features	***Electrodes***	***HE***	***FM***	***HA***	***FZ***	***HK***	***FK***
ACC mu	CPz	-0.26	**0.55** *	0.05	0.09	**0.43** *	0.19
	FCz	0.19	-0.10	0.00	-0.18	0.30	0.03
	Cz	-0.25	**0.37**	-0.21	-0.23	-0.05	0.06
Frontal alpha asymmetry	FP1-FP2	**-0.37**	0.09	-0.01	0.04	0.22	0.23
	AFP5-AFP6	-0.29	-0.05	-0.19	0.00	-0.16	-0.03
	AF7-AF8	-0.09	0.02	**-0.42** *	0.01	0.16	0.05
	AF5-AF6	0.20	0.12	0.07	0.18	**0.42** *	0.24
	AF3-AF4	0.04	-0.26	**0.40**	-0.01	0.12	**-0.40**
	AF1-AF2	-0.15	-0.13	**-0.30**	-0.10	-0.19	0.22
	F7-F8	0.14	-0.14	-0.01	**0.31**	**0.36**	0.18
	F5-F6	0.04	0.24	-0.21	**0.48** *	0.28	**0.39**
	F3-F4	-0.07	0.28	-0.13	**0.36**	0.09	0.11
	F1-F2	0.11	-0.16	-0.13	0.09	0.26	0.24
Prefrontal alpha asymmetry	FP1-FP2	**-0.37**	0.09	-0.01	0.04	0.22	0.23
	AFP5-AFP6	-0.29	-0.05	-0.19	0.00	-0.16	-0.03
	AF7-AF8	-0.09	0.02	**-0.42** *	0.01	0.16	0.05
	AF5-AF6	0.20	0.12	0.07	0.18	**0.42** *	0.24
	AF3-AF4	0.04	-0.26	**0.40**	-0.01	0.12	**-0.40**
	AF1-AF2	-0.15	-0.13	**-0.30**	-0.10	-0.19	0.22
ACC TBR	CPz	0.22	-0.06	-0.25	0.00	0.01	0.27
	FCz	**0.37**	-0.03	0.01	-0.12	0.17	0.04
	Cz	0.04	**-0.32**	-0.02	-0.29	**-0.47** *	0.19
Parietal beta	PO7	0.05	-0.10	0.12	-0.05	-0.27	**-0.47** *
	PO5	0.02	-0.26	0.02	-0.12	**-0.38**	**-0.48** *
	PO3	-0.13	**-0.38**	0.02	-0.24	**-0.48** *	**-0.54** *
	PO1	-0.19	**-0.39**	0.04	-0.28	**-0.44** *	**-0.56** *
	Poz	**-0.31**	**0.36**	0.07	0.19	0.27	-0.05
	PO2	**-0.35**	**0.33**	0.10	0.17	0.22	-0.10
	PO4	**-0.40**	0.28	0.14	0.11	0.11	-0.15
	PO6	**-0.37**	**0.34**	0.10	-0.09	0.01	0.02
	PO8	**-0.32**	0.14	-0.04	**-0.34**	0.00	-0.26
Temporal gamma	FT7	-0.17	-0.03	0.04	-0.25	-0.28	**-0.36**
	T7	-0.10	-0.12	-0.01	-0.23	-0.27	**-0.36**
	TP7	0.22	0.23	0.22	0.20	0.24	0.07
	FT8	0.00	-0.21	0.03	-0.28	-0.11	**-0.33**
	T8	-0.19	-0.20	-0.01	-0.23	-0.12	**-0.30**
	TP8	-0.27	-0.23	0.15	**-0.33**	-0.22	**-0.34**

Table 7.4: Correlation coefficients between motivation variables and EEG features from the regression model

Features	***Electrodes***	***HE***	***FM***	***HA***	***FZ***	***FK***
ACC mu	CPz	0.24	-0.15	0.14	-0.16	0.20
	FCz	0.16	-0.14	0.26	0.17	0.09
	Cz	0.16	-0.11	0.22	0.08	0.21
Frontal alpha asymmetry	FP1-FP2	0.02	0.19	0.00	-0.28	-0.25
	AFP5-AFP6	-0.08	0.22	-0.04	0.27	0.20
	AF7-AF8	-0.21	-0.08	-0.28	0.26	**0.32**
	AF5-AF6	-0.23	-0.26	-0.03	-0.16	**0.57** *
	AF3-AF4	-0.18	-0.29	-0.29	0.28	-0.09
	AF1-AF2	-0.29	-0.08	0.27	0.26	-0.26
	F7-F8	0.06	-0.13	0.05	-0.17	**0.50** *
	F5-F6	-0.23	0.19	**-0.47** *	0.12	**0.33**
	F3-F4	-0.29	**0.36**	**-0.51** *	-0.01	0.03
	F1-F2	**-0.41**	-0.12	0.06	0.00	0.25
Prefrontal alpha asymmetry	FP1-FP2	0.02	0.19	0.00	-0.28	-0.25
	AFP5-AFP6	-0.08	0.22	-0.04	0.27	0.20
	AF7-AF8	-0.21	-0.08	-0.28	0.26	**0.32**
	AF5-AF6	-0.23	-0.26	-0.03	-0.16	**0.57** *
	AF3-AF4	-0.18	-0.29	-0.29	0.28	-0.09
	AF1-AF2	-0.29	-0.08	0.27	0.26	-0.26
ACC TBR	CPz	0.16	0.22	-0.03	-0.24	**0.39**
	FCz	0.10	**-0.41**	-0.08	**-0.46** *	0.10
	Cz	0.25	**0.35**	0.15	-0.03	-0.24
ACC ERN (Money)	CPz	0.14	0.23	-0.27	**-0.36**	-0.01
	FCz	-0.09	0.21	-0.22	0.03	-0.15
	Cz	0.11	0.17	**-0.31**	**-0.31**	-0.07
ACC ERN (Satisfaction)	CPz	**0.36**	0.27	0.18	-0.05	0.08
	FCz	**0.30**	0.11	**-0.37**	0.04	-0.21
	Cz	0.15	0.22	0.06	0.03	0.00
ACC MFN (Money)	CPz	0.05	0.16	**-0.33**	**-0.32**	-0.16
	FCz	-0.12	0.20	**-0.30**	-0.05	-0.25
	Cz	-0.09	0.02	**-0.44** *	**-0.36**	-0.24
ACC MFN (Satisfaction)	CPz	0.18	0.28	0.27	-0.04	0.23
	FCz	0.08	**0.40**	-0.22	0.10	0.16
	Cz	0.02	0.27	0.02	0.05	0.22
ACC P300 (Money)	CPz	-0.21	**0.30**	-0.15	-0.23	0.06
	FCz	0.25	**0.40**	-0.14	-0.11	-0.11
	Cz	-0.22	0.16	-0.27	-0.27	-0.08
ACC P300 (Satisfaction)	CPz	-0.01	**0.31**	-0.07	-0.23	0.08
	FCz	-0.06	**0.34**	-0.25	0.11	0.09
	Cz	-0.18	0.22	-0.05	-0.20	0.15
Parietal beta	PO7	0.06	-0.27	-0.02	**-0.30**	0.19
	PO5	-0.01	**-0.37**	0.07	**-0.31**	0.29
	PO3	0.09	-0.27	0.18	**-0.40**	0.13
	PO1	0.04	**-0.31**	0.18	**-0.37**	0.00
	Poz	-0.01	-0.22	0.17	**-0.31**	0.09
	PO2	-0.15	-0.05	0.18	**-0.30**	0.04
	PO4	-0.20	0.03	0.18	**-0.33**	0.20
	PO6	-0.19	0.12	0.05	-0.01	0.18
	PO8	0.14	-0.21	0.17	-0.12	0.12
Temporal gamma	FT7	0.02	-0.17	0.14	**-0.38**	0.11
	T7	0.10	-0.16	0.13	**-0.32**	0.11
	TP7	0.10	-0.22	0.10	**-0.44** *	0.01
	FT8	0.09	-0.13	0.16	-0.14	0.13
	T8	0.08	-0.11	0.15	-0.26	0.12
	TP8	-0.05	0.14	0.03	**-0.43** *	0.23

during money feedback had a negative relationship with hope for social acceptance. Temporal gamma had a negative relationship with fear of rejection.

7.2.5 Discussion

We examined the proposed conceptual models using EEG signals from the IPP, SNP and regression model. In the IPP, most EEG features were validated to have relationships with motivation variables except ACC mu (no electrode), temporal gamma (no electrode) and ACC ERN (no electrodes). There were negative relationships between frontal alpha asymmetry and ACC TBR with some motivation variables. Also, there were positive relationships between frontal alpha asymmetry, prefrontal alpha asymmetry, ACC MFN during satisfaction feedback, ACC P300 during satisfaction feedback and parietal beta with some motivation variables.

In the SNP, frontal alpha asymmetry, prefrontal alpha asymmetry, parietal beta and temporal gamma from the SNP had relationships with motivation variables, except the temporal gamma had no related electrode. In addition, ACC mu, frontal alpha asymmetry, prefrontal alpha asymmetry have positive relationships with player motivation. Frontal alpha asymmetry, prefrontal alpha asymmetry and parietal beta had negative relationships with player motivation.

Finally, most EEG features from the regression model examined were found to be related to player motivation except ACC mu band, ACC ERN, ACC P300 and parietal beta. Furthermore, frontal alpha asymmetry, ACC TBR, ACC MFN during money feedback and temporal gamma had negative relationships, while frontal alpha asymmetry and prefrontal alpha asymmetry had positive relationships with motivation variables.

In conclusion, a summary of the EEG features proposed in conceptual models (see Fig. 7.2) are validated using EEG signals from the IPP, SNP and regression model. Results indicate that most EEG features are useful for assessing player motivation, except the ACC mu band and ACC TBR.

7.3 Identifying EEG Features for Assessing Player Motivation using Machine Learning

The EEG features from the literature have been examined in Section 7.2. However, it is possible that there are other EEG features that could be used to classify player motivation. In addition to drawing on existing EEG features from the literature, this section uses machine learning to consider a wider range of EEG features that allows for differentiating motive profiles. Temporal, spectral, time-frequency and asymmetry features were extracted and were selected by correlation subset evaluation methods. The KNN method was utilized as the classifier to examine the EEG features. Results showed that across different parts of the game, frontal alpha and temporal gamma are possible EEG indicators for assessing player motivation. Combining results from conceptual models and machine learning approaches, frontal alpha, several ACC ERPs and temporal gamma could be the possible EEG features for assessing player motivation.

7.3.1 Aim

The aim of this study is to explore possible EEG features other than those suggested by the literature for identifying achievement, affiliation and power motivation. We also hope to find related EEG features that correspond to different brain regions for player motivation in the different parts of our mini-game.

7.3.2 Hypothesis

We hypothesise that machine learning techniques will confirm the EEG features proposed in the literature. In addition, we hypothesise that there are other EEG features besides the features drawn from the literature that can be used for identifying achievement, affiliation and power motivation.

7.3.3 Method

Subjects were labelled according to LS3 from Chapter 5 for achievement, affiliation and power. With this subject labelling scheme, an investigation of a wide range of EEG features in player motive profiles was performed. It began with the extraction of different EEG features, followed by feature selection based on a correlation subset evaluation method (the comparison of various feature selection approaches is discussed in Appendix E). KNN was employed to evaluate the performance of selected features. In this experiment, we also utilised three parts of the EEG signals, which are from the IPP, SNP and a regression model, to explore possible EEG features for differentiating player motivation.

7.3.3.1 Feature Extraction

As shown in Chapter 6 and Section 7.2, several temporal features (ACC MFN, ACC ERN and P300), spectral features (ACC mu band) and asymmetry features (frontal alpha asymmetry) have the possibilities to identify player motive profiles and corresponding risk-taking and social attitudes. So in this section, we explore a wide range of EEG features by extracting temporal, spectral, time-frequency and asymmetry features from all EEG channels. As described in Sections 5.2.3 and 5.2.4, after pre-processing, recordings were segmented in 20 trials both in the IPP and SNP. Each trial comprised a 2.5s time interval including 500ms for baseline, 1.5s for players' actions, money and satisfaction feedback, and a 500ms buffer zone. EEG features were extracted on the basis of trials, the details of which are elaborated below.

Temporal features Three kinds of temporal features for EEG signals were considered: the mean of the EEG signal, the standard deviation of EEG signals and the peak-to-peak amplitude of EEG signals. The average and standard deviation of EEG time-series signals from the trials were calculated both for the IPP and SNP. In addition, the average peak-to-peak amplitude from the trials was included in the feature set. The peak-to-peak amplitude is the difference between the maximum amplitude and the minimum amplitude in EEG signals.

Spectral features To analyse spectral features, we extracted power spectral density (PSD) from different frequency bands using FFT and Welch's method [158]. Welch's method splits the EEG signals into segments with or without overlapping. Each segment was windowed with a Hamming window. The modified periodograms were averaged to obtain the PSD estimate. In this experiment, the PSD of EEG signals was estimated using a 250 point FFT and Welch's method of 1s time windows without overlapping. Five frequency bands of PSD were extracted in 64 electrodes that are delta (1-3Hz), theta (4-7Hz), alpha (8-12Hz), beta (13-31Hz) and gamma (32-42Hz).

Time-frequency features Because of the non-stationarity of EEG signals, we considered time-frequency features that capture two dimensions of EEG dynamics. To extract the corresponding EEG features in the IPP and SNP, we calculated the features using a 500 ms sliding window without overlapping in each trial. We divided each trial into 5 time windows, and the mean values extracted from those sliding windows were used as a trial's feature, that is 5 time windows $\times$ 64 channels for each subject.

We selected time-frequency features described in Section 5.2.4. The proposed model is based on the 10-20 system. However, we used a HD 72 EEG device that has 64 channels based on the 10-10 system, so we updated the electrodes into the high-density system. The frontal region comprises electrodes FP1, FP2, FPz, AFP5, AFP6, AF7, AF3, AF1, AFz, AF2, AF4, AF6, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8; the pre-frontal region comprises electrodes FP1, FP2, FPz, AF7, AF5, AF3, AF1, AFz, AF2, AF4, AF6 and AF8; the ACC comprises electrodes Fz, FCz and Cz, the parietal region comprises electrodes PO7, PO5, PO3, PO1, POz, PO2, PO4, PO6, PO8, POO7, POO8, O1, O2 and Oz; the temporal region comprises electrodes FT7, T7, TP7, FT8, T8 and TP8.

Time-frequency features were calculated by complex wavelet transform and decibel normalisation was utilised. Time-frequency features were divided into five frequency bands: delta band (1-4Hz), theta band (4-7Hz), alpha/mu band (8-12Hz), beta band (13-31Hz) and gamma band (32-42Hz).

Asymmetry features Literature has shown the importance of frontal alpha asymmetry in EEG-based emotion and motivation recognition. Therefore we regarded asymmetry features as part of our feature set. Asymmetry features were derived from the differences between the left and right hemisphere, thus a positive value means greater left than right, and a negative value means greater right than left. The electrode pairs for frontal alpha are FP1-FP2, AFP5-AFP6, AF7-AF8, AF5-AF6, AF3-AF4, AF1-AF2, F7-F8, F5-F6, F3-F4, F1-F2, FT7-FT8, FC5-FC6, FC3-FC4, FC1-FC2, T7-F8, and for prefrontal alpha are FP1-FP2, AFP5-AFP6, AF7-AF8, AF5-AF6, AF3-AF4, AF1-AF2.

7.3.3.2 Feature Selection

Feature selection is an important step for generating an accurate predictive model. It is used to remove irrelevant and redundant features from the data that may have no influence or may decrease the accuracy of the model. Feature selection improves the prediction accuracy of the model, reducing the complexity of the model and making it easier to understand and compute. There are three kinds of feature selection methods: filter methods, wrapper methods and embedded methods [159]. A filter method is used as a pre-processing step. It applies a statistical measure to assign a score to each feature, then the features are ranked and a decision made to either keep or remove them from the feature set. Wrapper feature evaluation methods evaluate a set of features as a search problem and utilise a machine learning method to score subsets of variables according to classification performance. Embedded methods are included into the training process of other methods and usually select the features while the model is being built.

Table 7.5: Summary of the most effective EEG features for motivation classification identified using correlation subset evaluation in the individual play phase

	Accuracies	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Achievement	68% ± 19%		AF8_γ, AF6_γ	F5_θ, C5_θ, TP7_θ	F3_α, F1_γ
Affiliation	80% ± 15%	AF6_mean, F4_mean	FC2_γ	Fz_γ, POO8_γ	F5_δ, FC5_δ, FC5_α, PO7_α, PO1_α, AF1_β, PO1_β, POO7_β, FC3_γ
Power	71% ± 20%	F2_peak	AF6_δ, FT7_δ, C5_δ, Oz_δ, C5_θ, AF7_α, FPz_α, C5_α, C5_γ, PO8_γ		F3_δ, C5_δ, TP7_θ, FC3_γ, C1_γ

Correlation subset evaluation methods evaluate a subset of features by considering each feature together with the degree of redundancy between variables [160]. In this method, subsets of features that are highly correlated with the class and show low inter-correlation are selected. It employs a best-first searching approach that searches the feature subset by greedy hill-climbing, augmented with a backtracking facility.

To select EEG features for identifying player motivation, a correlation subset evaluation method was employed. A comparison between different feature selection methods (as shown in Appendix E) showed the effectiveness of the correlation subset evaluation method. The multiple perspectives of performance between different EEG features, including different channels, different brain regions, different feature types and different frequency bands are discussed in this section. The results are presented both for the IPP, SNP and the parts of the game selected by the regression model in Chapter 6.

Table 7.6: Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the individual play phase

	Features	***Brain regions***
Achievement	Theta band	Left temporal
	Alpha band	Frontal asymmetry
	Gamma band	Frontal, frontal asymmetry
Affiliation	Delta band	left temporal
	Alpha band	Parietal, left temporal
	Beta band	Parietal, frontal
	Gamma band	Central, parietal
Power	Delta band	Left temporal, frontal and parietal
	Theta band	Left temporal
	Alpha band	Prefrontal, left temporal
	Gamma band	Left temporal, central and parietal

7.3.4 Results

We first selected features using EEG signals from the IPP. Tab. 7.5 presents EEG features using correlation subset evaluation in the IPP. From the table, we can see that for achievement motivation, spectral, time-frequency and asymmetry feature types had almost equal numbers of selected features. This is in contract to affiliation motivation for which more asymmetry features are selected than the other three feature types. As for power motivation, more spectral features contributed to player motive profiling, followed by asymmetry features. Overall, spectral and asymmetry features were the most selected features for player motivation profiling in the IPP.

We summarise the frequency bands and brain regions for achievement, affiliation and power motivation in Tab. 7.6. It shows that the theta, alpha and gamma bands were selected for identifying achievement motivation. Also, the delta, alpha, beta and gamma bands were chosen for identifying affiliation motivation. Lastly, the delta, theta, alpha, gamma bands were selected as the relevant frequency bands for classifying power motivation. In terms of brain regions, the frontal and left temporal regions were the significant brain regions for achievement. For affiliation, frontal, left temporal, parietal and ACC were the related brain regions. Power motivation was identified in the frontal, left temporal, parietal and ACC brain regions as well. Thus, alpha and gamma were the common frequency bands across the three motivations. As for brain regions, we concluded that the frontal and left temporal regions were

Table 7.7: Summary of the most effective EEG features for motivation classification identified using correlation subset evaluation in the social network phase

	Accuracies	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Achievement	72% ± 22%	AF6_mean, F7_mean, FT7_mean, C3_mean, CP3_mean, CPz_mean	F8_δ, FC4_α	F8_δ, PO1_θ, AF4_δ, TP7_β, POO7_β	FC3_α, C3_β
Affiliation	71% ± 23%		FC2_δ, AF7_θ, FP2_β		
Power	77% ± 22%	C1_mean, TP8_mean, F7_peak	FT7_θ, F2_β	AF2_δ, PO5_α, CP5_β, CP6_γ	O1_δ

Table 7.8: Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the social network phase

	Features	***Brain regions***
Achievement	Delta band	Frontal
	Theta band	Parietal
	Alpha band	Frontal
	Beta band	Left temporal, parietal
Affiliation	Delta band	Frontal
	Theta band	Prefrontal
	Beta band	Prefrontal
Power	Delta band	Frontal and occipital
	Theta band	Left temporal
	Alpha band	Parietal
	Beta band	Frontal, left temporal
	Gamma	Right tempral

the most effective brain regions for identifying achievement, affiliation and power motivation.

In the SNP, we can see from Tab. 7.7 that more temporal and time-frequency features were selected to classify achievement motivation, while only spectral features were chosen for identifying affiliation motivation. Furthermore, temporal and time-frequency features were chosen for power motivation. We concluded that temporal, spectral and time-frequency features contributed equally to identifying player motivation in the SNP, except that asymmetry features seem to be irrelevant to achievement, affiliation and power motivation.

Table 7.9: Summary of the most effective EEG features for motivation classification using correlation subset evaluation in the regression model

	Accuracies	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Achievement	68% ± 18%		AF8_γ, AF6_γ	F5_θ, C5_θ, TP7_θ	F3_α, F1_γ
Affiliation	80% ± 17%	FPz_mean, AF3_mean, F4_mean		PO5_θ, POO8_γ	F3_α, FC5_α, POO7_α, AF1_β, FC3_γ
Power	77% ± 22%	AF6_mean, F3_mean, PO3_mean	AFz_δ, AF6_δ, FT7_θ, FP1_α, F8_α, C3_α, C3_β, CP5_β, O1_β	PO6_γ	POO7_δ, C1_α

We also summarise that frequency bands and brain regions are useful for identifying achievement, affiliation and power motivation in the SNP, as shown in Tab. 7.8. For achievement motivation, the delta, theta, alpha and beta bands were selected as the related frequency bands. On the other hand, the delta, theta and beta bands were also chosen for classifying affiliation motivation. Lastly, power motivation had delta, theta, alpha, beta and gamma bands as the relevant frequency bands. Overall, delta, theta and beta bands were the common frequency bands across the three motivations. In terms of brain regions, frontal, parietal and left temporal were the significant brain regions for identifying achievement motivation. For affiliation motivation, the frontal region was the most relevant brain region. For power motivation, frontal, temporal, central, occipital and parietal were the relevant brain regions. Therefore, the common brain regions useful for identifying achievement, affiliation and power motivation were frontal, left temporal and parietal regions.

Focusing on a subset of NPCs from the regression model, we selected EEG features using the correlation subset features selection method. As shown in Tab. 7.9, spectral, time-frequency and asymmetry contributed equally to achievement motivation. As for affiliation motivation, asymmetry features were the most selected feature type, followed by temporal and time-frequency features. Power motivation

Table 7.10: Summary of the most effective frequency bands and brain regions for achievement, affiliation and power motivation in the regression model

	Features	*Brain regions*
Achievement	Theta band	Frontal, left temporal
	Alpha band	Frontal
	Gamma band	Frontal
Affiliation	Theta band	Parietal
	Alpha band	Frontal, left temporal, parietal
	Beta band	Frontal
	Gamma band	Parietal, left temporal
Power	Delta band	Frontal, parietal
	Theta band	Left temporal
	Alpha band	Frontal, Center
	Beta band	Left temporal, occipital
	Gamma band	Parietal

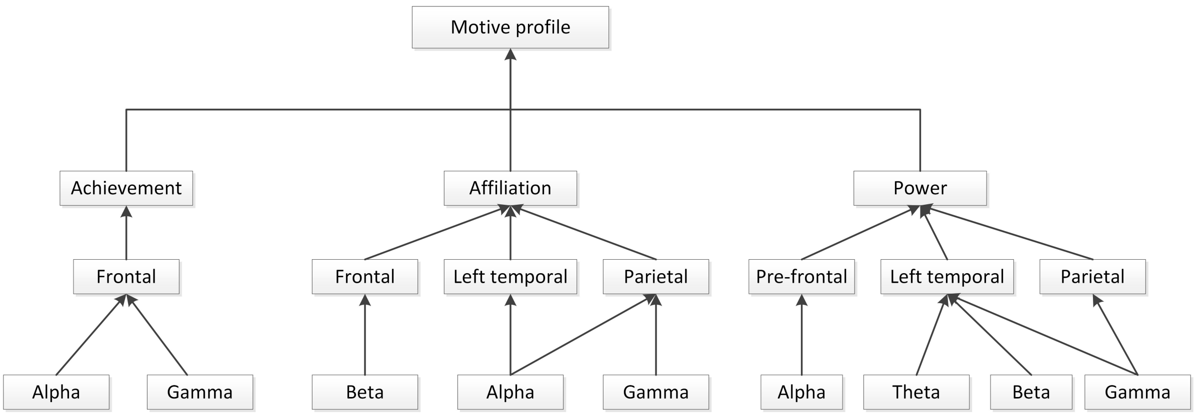


Figure 7.3: Relevant brain regions and frequency bands for assessing achievement, affiliation and power motivation in the abstract mini-game

used spectral features the most, rather than temporal, time-frequency and asymmetry features. Overall, spectral and asymmetry features were the most selected feature types for player motivation profiling using EEG signals from the regression model.

We also summarise the frequency bands and brain regions in Tab. 7.10. Theta, alpha and gamma bands were the significant frequency bands for achievement motivation, while theta, alpha, beta and gamma frequency bands were selected for affiliation motivation. For power motivation, delta, theta, alpha, beta and gamma were identified as the related frequency bands. According to brain regions, frontal, left temporal were identified as the brain regions for achievement motivation. EEG features for affiliation motivation were expressed in frontal, parietal, left temporal brain regions. Power motivation was identified in frontal, parietal, left temporal, central and occipital brain regions. Therefore, we concluded that theta, alpha and gamma were the common frequency bands for the regression model, while frontal and left temporal were the general brain regions for achievement, affiliation and power motivation.

7.3.5 Discussion

To summarise the EEG features from different phases of the mini-game, Fig. 7.3 is presented to show the brain regions and frequency bands of selected features. From Fig. 7.3 we can see that frontal alpha and frontal gamma are the most useful EEG features for assessing achievement motivation across three different parts of our mini-game. Frontal beta, parietal alpha, left temporal alpha and parietal gamma are the most selected EEG features for assessing affiliation. Finally, we can observe from Fig. 7.3 that pre-frontal alpha, left temporal theta, left temporal beta, left temporal gamma and parietal gamma are the most selected EEG features for power motivation. In summary, frontal, temporal and parietal regions are the most relevant brain regions, and alpha, gamma and beta are the most relevant frequency bands.

As discussion in Section 7.2, we concluded that the EEG features from the literature have relationships with motivation variables. Specifically, frontal alpha asymmetry, pre-frontal alpha asymmetry, ACC ERN, ACC MFN, ACC P300, parietal beta and temporal gamma are identified for assessing player motivation.

When comparing the findings from both literature based and machine learning-based methods, we observed that frontal alpha, temporal gamma and ERPs in ACC are the most effective EEG features for identifying player motivation.

The frontal alpha, which is recognized as a significant feature for player motive profiling, is also treated as the major frequency band in emotion recognition [108, 109]. Relatively higher left frontal alpha represents positive emotion and approach motivation, while relatively higher right frontal alpha reflects negative emotion and withdrawal motivation [91, 110]. The effectiveness of prefrontal alpha asymmetry is also examined in EEG recognition of risk-taking and decision-making behaviour, which shows that relative right-sided frontal activity is associated with the riskier strategies [119, 125]. Moreover, EEG studies of social behaviour also examined the relationship between medial prefrontal alpha activity and social attitudes [127, 133] . According to psychological motivation theory, achievement, affiliation and power motivation have different characteristics of risk-taking, social attitudes and emotion, thus it is reasonable that there are common features across these cognitive and emotional states.

Furthermore, results indicated that several ERPs (e.g. ACC ERN, ACC MFN and ACC P300) are effective indicators for assessing player motives, which is consistent with EEG studies of risk-taking and social attitudes. In EEG studies of risk-taking attitude, ACC MFN often follows larger gains [119], and the ERN is related to risk-taking and strategic decision-making behaviour [49]. IIn EEG studies of social attitude, MFN and LPP are identified for assessing social behaviour [129]. Again, these ERPs are common features across motive profiles and corresponding characteristics.

7.4 Conclusion

This chapter not only validates the EEG features proposed in our conceptual model, but also explores a range of EEG features relating to motive profiles from the IPP, SNP and a regression model. According to our conceptual model, most EEG features are useful for assessing motivation except the ACC mu band and ACC TBR. In addition to our conceptual model, we explored a range of EEG features for identifying player motivation in different parts of our mini-game. The results showed that the frontal, temporal and parietal regions were the most relevant brain regions, and alpha, gamma and beta were the most effective frequency bands for assessing motivation. By analysing the findings from both approaches, we conclude that frontal alpha, temporal gamma and ERPs in ACC are useful for assessing achievement, affiliation and power motivation.

In the next chapter, we will conclude the findings of this thesis, and identify some possible directions for future work.

Chapter 8

Conclusions and Discussion

8.1 Introduction

Gameplay is a voluntary problem-solving process. Players take part in the process because of the feeling of fun that arises during gameplay. Because players have different personalities, playing preferences, abilities and motivation, the feeling of fun may mean different things to different people. Understanding player experience helps us design games that satisfy various player needs. Existing player models focus on emotion, cognition and behaviour, but motive profiles have not been fully studied. This thesis focuses on understanding and modelling achievement, affiliation and power motivation, because of their mappings with other player profiles. Also, theories of achievement, affiliation and power motivation are influential in psychology, forming the basis of three-need theory and three-factor theory. Existing motive measurements include subjective measurements like questionnaires, the TAT method, the MMG test, as well as objective measurements such as behaviour analysis. However, we still lack an automatic, objective measure for identifying player motive profiles. EEG measures brain signals during the gameplay without interrupting players and signals come from involuntary processes. Furthermore, achievement, affiliation and power motivation drive different behaviours relating to risk-taking, social attitude and emotion, which can be measured by EEG. Thus, EEG technology can be regarded as an objective and promising way to measure motive profiles.

To profile achievement, affiliation and power motivation using EEG signals, several challenges needed to be addressed. First, it required an appropriate game protocol to measure player motivations. This game scenario needed to be complex enough to evoke the characteristics of different motivations (risk-taking and social variables), but simple enough to control other irrelevant variables. In addition, a sound experimental scenario was needed to collect EEG signals for examining the hypothesis. It included how to design a neuroscience experiment to collect EEG signals properly, and what kinds of data needed to be collected. Lastly, suitable data analysis methods, especially an EEG signal processing approach needed to be adopted to analyse the data in order to validate the possibility for EEG profiling of these motivations. The work in this thesis has tackled these research challenges.

The remainder of this chapter includes a summary of this thesis. Research contributions and findings of this thesis are presented in Section 8.2. Limitations of this work and possible future directions are discussed in Section 8.3. Finally, Section 8.4 concludes this thesis.

8.2 Research Contributions and Findings

In this thesis, we presented a framework for using EEG signals to profile achievement, affiliation and power motivation in a game scenario. As introduced in Chapter 1, this thesis aims to answer four main research questions, making four contributions as follows:

Contribution 1 An abstract mini-game was designed as the platform to identify player motivation through EEG signals. The theme of the game is 'Friends or Fortune'. Prisoner's dilemma was adopted in the game as a strategic decision-making scenario evoking risk-taking and social attitudes to identify player motives. Four non-player characters were designed with a money dimension, satisfaction dimension and various PD play strategies. Players played with these NPCs through two phases of the mini-game: the individual play phase and social network phase. The proposed game scenario provides a medium to study EEG profiling of achievement, affiliation and power motivation, which could be used when studying human decision-making behaviour in human-machine interactions.

Finding 1 Results indicated the proposed mini-game has the potential to study achievement, affiliation and power motivation through characteristics of risk-taking and social factors. Simulation results led to the hypothesis that players with different motives may choose different play strategies when playing with different NPCs, to optimise money or satisfaction, or trade-off the features. Also, they will select different NPCs into their social network to satisfy their individual motivations like exploiting uncertainty and other opponents (power motivation), or earning money (achievement motivation) or maximizing NPC satisfaction (affiliation motivation). Our analysis of player behaviour and EEG signals suggested that the money and satisfaction dimensions of NPCs had the ability to reveal risk-taking and social attitudes respectively, and that play behaviour of NPCs also contributed to profiling player motivation. Both the IPP and SNP had the potential to identify motivation, but the IPP slightly outperformed the SNP for assessing player motivation.

Contribution 2 A human experiment was performed using the mini-game to collect player behaviour and EEG signals, and psychological data from the multi-motive grid test. The experimental scenario was designed with sound experimental protocol, EEG setup, procedure and data collection methodology. With the psychological test data as the ground truth, three subject labelling schemes were proposed. We also compared the performance of behaviour-based and EEG-based motive measurements. This not only identified the possibility of using EEG technology to profile player motivation, but also compared different approaches for measuring player motivation.

Finding 2 Three kinds of data were collected in this experiment, providing the numerical sources for understanding and assessing the relationships between different sources of data for player motivation profiling. A selection of demographic and statistical data from subjects showed the variations between the motive profiles (from MMG test), and their player behaviour and EEG data (from the game).

Contribution 3 We have demonstrated the potential for EEG-profiling of achievement,affiliation and power motivation while playing a game. We proposed the methodology for EEG signal processing and extracted time-frequency features and asymmetry features for motive profile classification. Correlation-based feature subset selection was utilised as the approach to feature selection, and K-nearest neighbours was used as the classifier. Subjects were labelled using three different subject labelling schemes of achievement, affiliation and power motive according to the relative strengths of the hope and fear components. Using the subject motive profile, we further validated the possibility of classifying each subject labelling scheme using player behaviour and EEG signals from the game scenario. This study used EEG technology as a tool to identify subject motive profile of achievement, affiliation and power, and may be applicable to the study of game design, player profiling, brain-computer interface and human-machine interactions.

Finding 3 The use of EEG signals for profiling achievement, affiliation and power motivation was found to work better than profiling which used player behaviour alone. When comparing three different subject labelling schemes, hope component generally classified more accurately than the fear component in the strength-based labelling scheme (LS1). As for the situation-based labelling schemes, LS3 (H-L, L-H and other) performed better than LS2 (H-L, L-H, H-H and L-L) in most cases. EEG signals in the SNP did not perform as well for affiliation motivation classification as did EEG signals in the IPP.

Contribution 4 Finally, EEG features for predicting mental states that can be indicators of achievement, affiliation and power motivation were identified using two approaches. The first one selected EEG features from the literature regarding EEG recognition of risk-taking, social and emotion, which are the characteristics of achievement, affiliation and power motivation. Correlation analysis was utilised to identify the corresponding EEG features. Furthermore, several temporal, spectral and time-frequency and asymmetry features were explored using machine-learning methods. Critical EEG features and brain regions were examined to relate to mental states and link to the motive profile. The significance of this work lies in its evaluation of EEG features for mental state indicators of motivation. These EEG features, are transferable to studies of human-machine interaction, player experience, player profiling and other AI research.

Finding 4 A range of EEG features was identified for assessing player motivation in different parts of our mini-game. Risk-taking, social attitudes and emotion are three mental states that can be used as indicators of motive profiles and measured by EEG signals. Using EEG signals from the game scenario, the critical EEG features for three mental states were examined using correlation analysis. The results showed that most of the EEG features proposed in our conceptual model were related to motivation variables from the MMG test, except ACC mu band and ACC TBR. Furthermore, after exploring possible EEG features for assessing player motivation, we have concluded that frontal, temporal and parietal are the useful brain regions, and alpha, gamma and beta are the useful EEG features. Our analysis of these findings identified frontal alpha, temporal gamma and ERPs in ACC as the most effective EEG features for assessing player motivation.

In summary, Contribution 1 addresses Research Question 1 of this thesis by proposing the game scenario for identifying achievement, affiliation and power motivation using EEG. It is explained in Chapter 3, and the design of our mini-game is validated in Chapter 6. Contribution 2 answers Question 2 by conducting a human experiment to use different approaches to collect data for assessing player motivation, which is elaborated in Chapter 4. Contribution 3 answers Question 2 by justifying the possibility of using EEG signals to classify motive profiles compared to player behaviour, which is presented in Chapter 5. Contribution 3 also deals with Question 3 by proposing a series of EEG signal processing procedures, described in Chapter 5. Contribution 4 addresses Question 4 by exploring the use of EEG features to assess the mental states of player motive profiles.

These findings support the conclusion that EEG technology can be a promising way to profile achievement, affiliation and power motivation in the proposed game scenario. Our investigations in this thesis explored the use of EEG technology for player motive profiling, and have provided a theoretical and empirical research basis for further investigations.

8.3 Limitations and Future Work

This thesis has examined the use of EEG technology to profile achievement, affiliation and power motives in the proposed game scenario. However, there are still some remaining research challenges that need to be addressed in future work.

Firstly, some short-term work should be done to improve EEG-profiling of motivations:

- We could further improve the game design to measure achievement, affiliation and power motivation more efficiently and appropriately. First, the risk-taking factor in the game scenario could be enhanced. The proposed game scenario uses the PD game to evoke a risk-taking element, which could be improved by using more gambling like choices. Moreover, the current SNP has no latency for money and satisfaction feedback when players play with their social network. Thus the design of SNP needs to be improved in future work.

- It may be worthwhile investigating the use of player behaviour features and EEG features collected from the game scenario to measure human motivation instead of using the MMG test. Subjects in this thesis are classified based on three subject labelling schemes, including high hope low fear, high fear low hope and other levels of each motivation. Future directions could be the identification of different motivation states, as illustrated by the MMG test (numerical output of six motivation variables). Data fusion technology could be utilised to identify player motivation from different sources of data.

There are several applications arising from the work presented in this thesis that could be developed in future studies:

- The study of EEG features related to risk-taking, social attitudes and emotion, could be applied to human-machine interaction research. Understanding the mental states of human operators and their decision-making preferences would encourage efficient human supervision in human-machine interaction. Individual differences in motivation impact the effectiveness and efficiency of human-machine interaction systems, and this could be a direction for future research.

- The abstract mini-game has the potential to sit within future multi-user games in more complex virtual worlds. The abstract game is generic enough that it could be adapted to fit as a part of a complex game with a new plot. However, there are still some challenges need to be addressed first. This includes re-design of the SNP and changes to or substitution of some of the characters in the IPP. Investigation would also be required to understand whether new artifacts introduced when players interact with a more complex game could be adequately compensated for. The controlled features are necessary for our experiments, and further experiments would be required to understand the impact of artifacts introduced from a more complex game environment, and whether these could be compensated for. Other challenges that need to be addressed before such experiments make sense include re-design of the SNP and changes to or substitution of some of the characters in the IPP.

- Understanding player motivation can explain why people act differently in the same situation and which part of the game people are most engaging with. A future study could incorporate an adaptive game environment to satisfy players' personal motivations dynamically. This could result in a more enjoyable and satisfying game experience for individual players and keep them in the flow zone for as long as possible.

8.4 Concluding Remarks

Understanding and modelling player motivations facilitates studies of player profiling, game design, human-machine interactions and AI. This thesis provides an alternative and promising way for EEG technology to measure achievement, affiliation and power motivation. Based on the literature review, three characteristics of achievement, affiliation and power motivation: risk-taking, social attitudes and emotion, can be measured by EEG. We designed a game scenario, incorporating risk-taking and social factors, to identify human motivation using EEG. By analysing behaviour data and EEG signals collected from the human experiment, the hypothesis that EEG technology can measure achievement, affiliation and power motive profile in the game scenario was validated. This thesis also identifies the corresponding EEG features that indicate risk-taking, social attitudes and emotion, which further relates to motive profiles. The work of this thesis forms a solid foundation for different directions of future research.

Appendix A

Friends or Fortune? A Social Network Game Booklet

A.1 Introduction

This section displays the booklet of our proposed mini-game. The booklet is displayed during the experiment to instruct subjects in how to play the game. It consists of three sections: Section A Introduction, Section B Tutorial Phase and Section C Game Phase. Section A introduces the game storyline and our four characters. Section B shows the tutorial phase that is used to instruct players to play with four NPCs, understand their play strategies, and how to play with them to earn money or maintain satisfaction. Finally, Section C describes the process of the game phase. It starts with a survey, followed by an individual play phase and ends with a social network phase.

University of New South Wales, Canberra

Never Stand Still

School of Engineering and Information Technology – Trusted Autonomy Group

Friends or Fortune?
A Social Network Game
Booklet

Trust Autonomy Group
School of Engineering and Information Technology
University of New South Wales
Australian Defence Force Academy

Contents

SECTION A

INTRODUCTION---------------5

1. Friends or fortune?------------5

2. The game----------------------- 5

3. Meet the Characters---------- 6

SECTION B

TUTORIAL PHASE------------ 7

1. Play with characters----------7

   Cooperater Candy------------7

   Defector Dan------------------10

   Random Ruby-----------------11

   Vengeful Vince ---------------12

2. Check your understand-----14

   Tasks----------------------------14

SECTION C

Game Phase -----------------15

1. Survey-------------------------15

1. Free-play----------------------16

2. Social network--------------- 17

   Team up-----------------------17

   Add characters----------------17

   Play----------------------------19

   Subjective feedback--------19

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Section A
Introduction

Friends or Fortune?

In this game, you will meet four virtual characters who approach their virtual lives with different strategies. First, you will get to know them individually, by playing a game with them. After that you will have the opportunity to team up to make friends or fortune. You choose.

The Game

In the game you will play, each player can earn their ‘fortune’ or build their ‘friendship’ by choosing to cooperate or defect. The friendships and fortunes of each player depend on the choices of both players. This is what happens when…

You cooperate AND Opponent cooperates $ 300 / $ 300	You defect AND Opponent cooperates $ 500 / $ 0
You cooperate AND Opponent defects $ 0 / $500	You defect AND Opponent defects $ 100 / $ 100

You can satisfy your opponent by allowing them to earn as least or as much as you. They tend to be your friends if you allow them to earn more money than you. You will lose your friendships when you earn more money than them. Now let’s meet the characters…

Meet the characters

Like you, the virtual characters can earn money, and feel satisfied or unsatisfied depending on the outcome of the game. Here's how they think:

Cooperator Candy

Candy is satisfied and tends to be your friend when she cooperates and earns the greatest share of the money. Candy always cooperates.

Defector Dan

Dan is satisfied and tends to be your friend when he defects and earns the greatest share of the money. Dan always defects.

Random Ruby

Ruby is satisfied and tends to be your friend when she earns the greatest share of the money, but has equal preference for cooperation and defection. Ruby chooses to cooperate or defect at random.

Vengeful Vince

Vince is satisfied and tends to be your friend when he earns the greatest share of the money. Vince will cooperate at first, and as long as his opponent cooperates. However, if his opponent defects, he will take revenge by defecting in the next round. He always chooses the same action his opponent chose in the previous round.

All the characters' satisfaction is amplified by the size of the social network they belong to.

Now you know the characters. How will you play them? For friendship or fortune…?

First, let's take a tutorial to learn more…

Section B

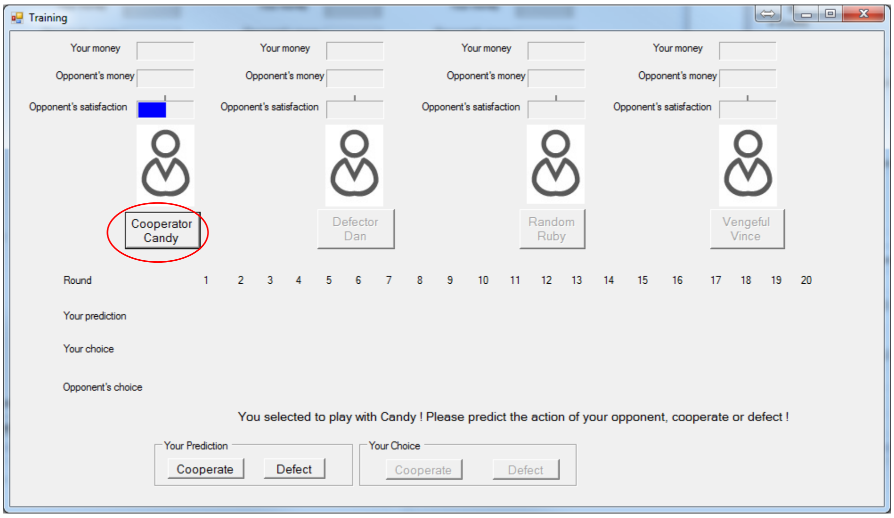
Tutorial Phase

This tutorial aims to help you learn more about the characters. Firstly, you need to play with each character by following our instructions. Then you will have an opportunity to demonstrate your understandings of the characters.

Play with the characters

Cooperator Candy

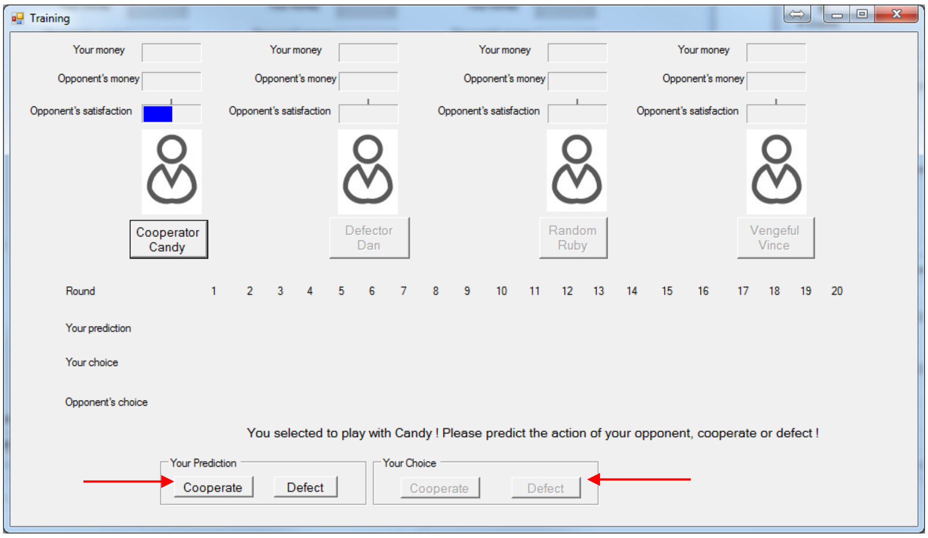
On the tutorial screen, you can see the four characters. Above them, are your money progress bar, your opponent's money progress bar and your opponent's satisfaction bar. These progress bars indicate your results with each character. Now follow the steps to finish the tutorial…



1. **Click the Cooperator Candy button, then you can see Candy is activated. Your money and opponent's money start with nothing, but it may increase according to your choices. While opponent's satisfaction begins with neutral, it may increase or decrease based on your choices.**

2. Predict Candy's choice will be cooperation by clicking the **Cooperate** button in the **Your Prediction** box. See your prediction appear in the interface.

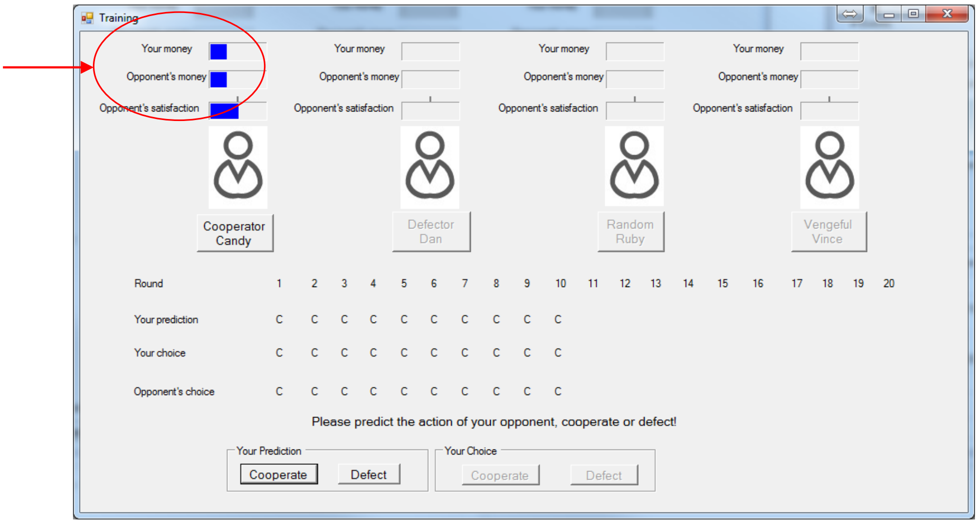
3. Click the **Cooperate** button in the **Your Choice** box to cooperate with Candy.



4. While you were doing this, Candy also chose to cooperate.

5. Observe the bars above Candy. You can see that both you and Candy won the same amount of money. Your money progress bar and Candy's money progress bar slightly increase. Also, Candy's satisfaction remains the same.

6. Now cooperate with Candy for the next nine rounds.

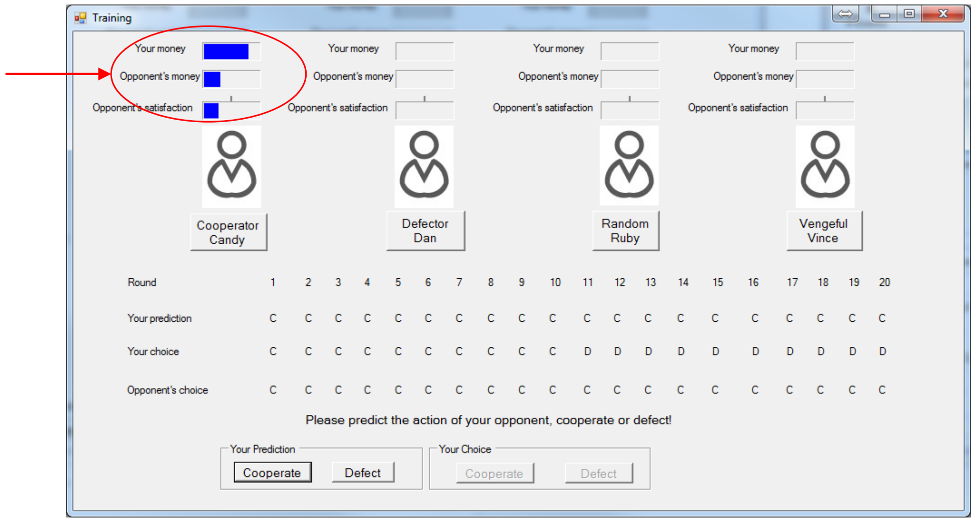


7. In round 11, defect against Candy by clicking the **Defect** button in the **Your Choice** box. You can see Candy still chooses to cooperate.

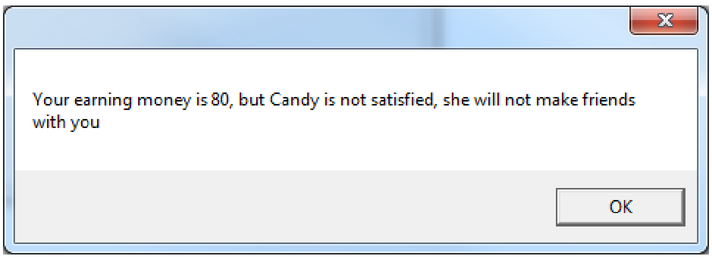
8. Observe your money increase while Candy earns nothing.

9. See her satisfaction level decrease. The value of her satisfaction bar is now below the neutral level. She probably will not make friends with you.

10. Defect against Candy for the next nine rounds.



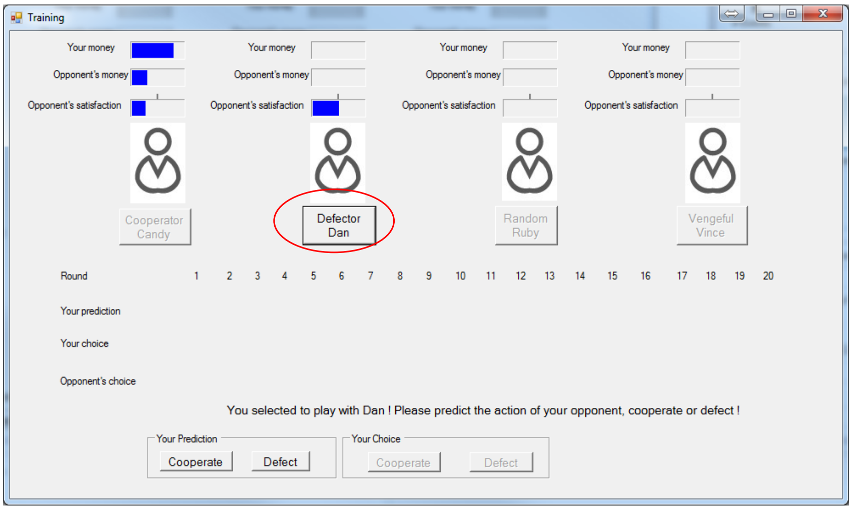
11. After twenty rounds, see your playing results with Candy in the pop-up window. You have earned a lot of money, while Candy will not make friends with you.



Defector Dan

Now it is the time to face Defector Dan…

1. Press the Defector Dan button, and start to play with Dan. You can see his satisfaction progress bar starts with neutral.



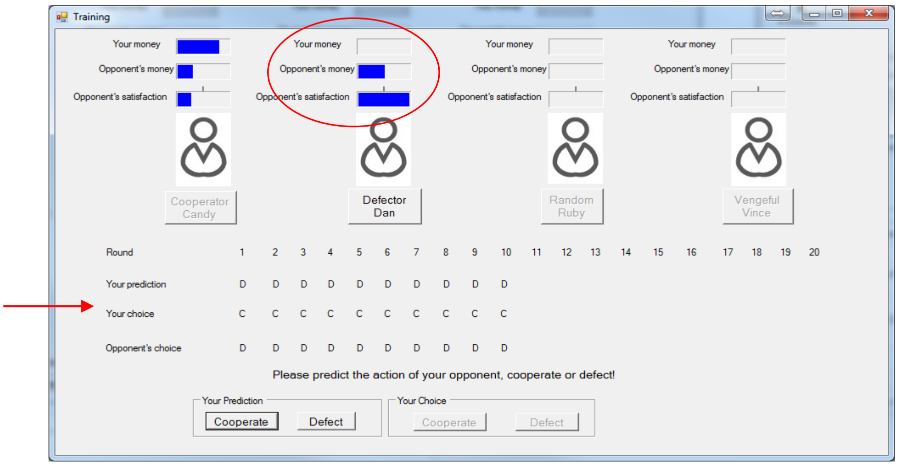
2. Predict Dan's choices will be defection by clicking the Defect button in the Your Prediction box.

3. Click the Cooperate button in the Your Choice box to cooperate with Dan.

4. See that you earn nothing, while Dan's money increases.

5. Observe Dan's satisfaction value is now above the neutral level. He would like to make friends with you.

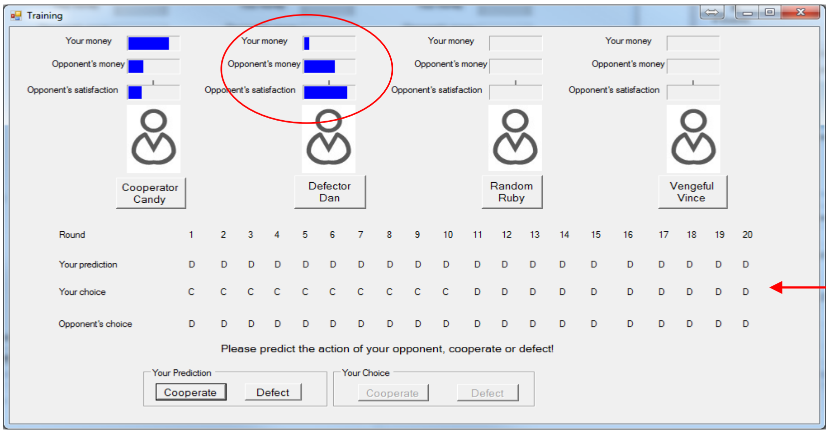
6. Play with Dan by cooperating for the next nine rounds and see the result.



7. In the round 11, defect against Dan by clicking the **Defect** button in the **Your Choice** box.

8. Observe both of you money slightly increases, but Dan’s satisfaction level does not change.

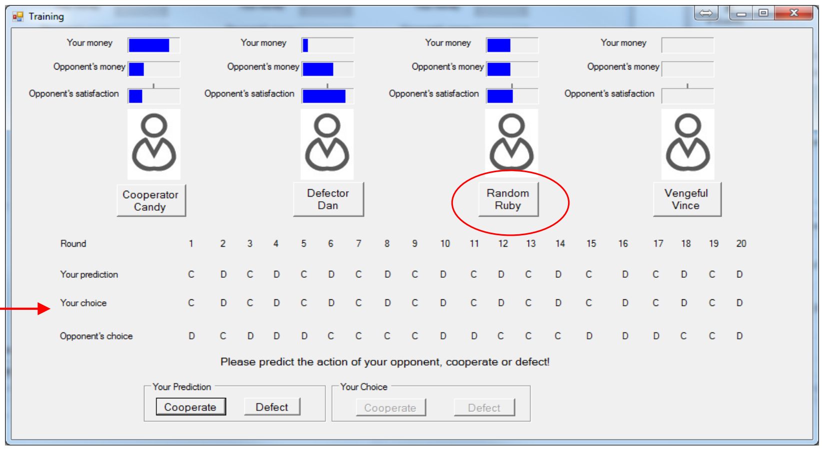
9. Defect against Dan for the next nine rounds.



Random Ruby

Now Random Ruby comes!

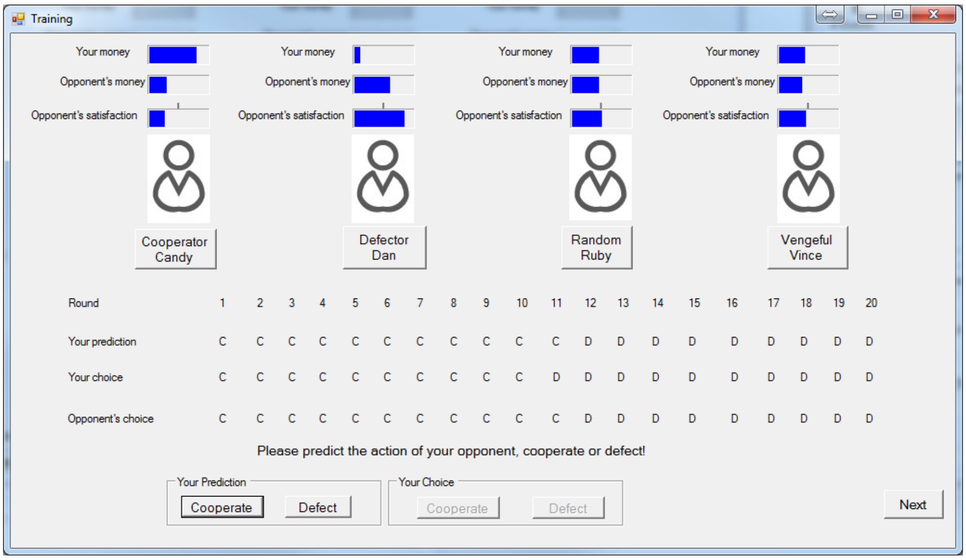
1. Press the **Random Ruby** button to play with her.
2. Ruby’s behaviour is random, try to predict what she will do.
3. Cooperate with her for the first ten rounds, and defect against her in the next ten rounds, see what you get.



Vengeful Vince

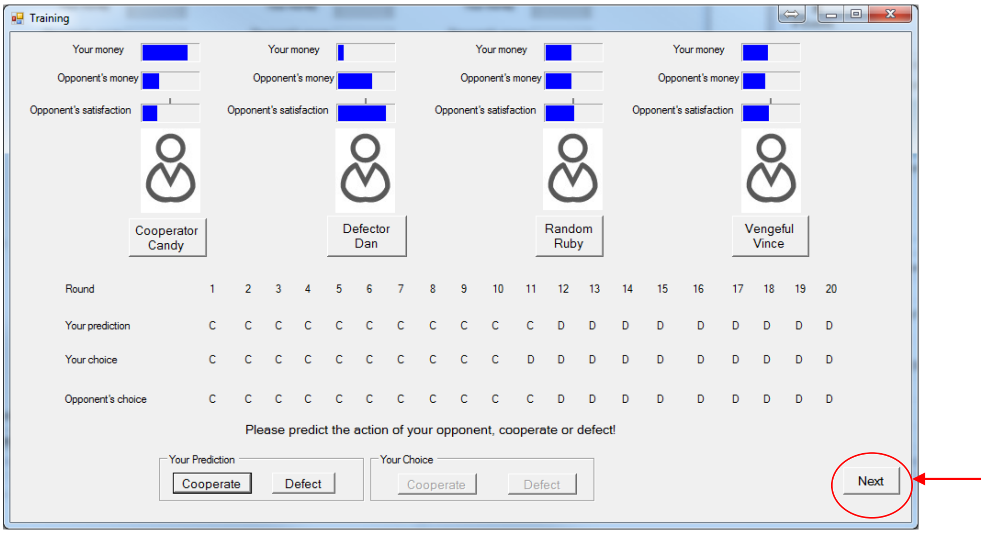
Now you can play with Vengeful Vince by press the <u>Vengeful Vince</u> button…

1. **Predict Vince's choice will be cooperation by clicking the corresponding button.**
2. **Cooperate with Vince by clicking the <u>Cooperate</u> button in the <u>Your Choice</u> box.**
3. **See Vince also cooperates with you in the first round.**
4. **Both of your money increases and his satisfaction level stays the same.**
5. **Now cooperate with Vince for the next nine rounds. See that he always chooses your action as his next action.**
6. **In round 11, defect against Vince, you can see he also defects against you.**
7. **Observe that both of your money increases, but less than when you cooperate. His satisfaction level is still the same.**
8. **Defect against Vince for the remaining nine rounds.**



Congratulations! You have played with the four characters and now it's time to show your understandings of the characters!

Please press the Next button to have a go….



Now check your understand ...

Now we have four tasks so that you can check your understanding.

Follow our instructions to complete these tasks….

<u>Task 1</u>

a) Play with Cooperator Candy to maintain her satisfaction level for ten rounds.

b) Play the next ten rounds to maximize your earnings.

<u>Task 2</u>

a) Play with Defector Dan to maximize his satisfaction level for ten rounds.

b) Play the next ten rounds to increase your earnings.

<u>Task 3</u>

Play with Random Ruby, and try to predict her choices.

<u>Task 4</u>

a) Play with Vengeful Vince to maximize your money and maintain his satisfaction level for ten rounds.

b) Play the next ten rounds to earn money and maintain his satisfaction.

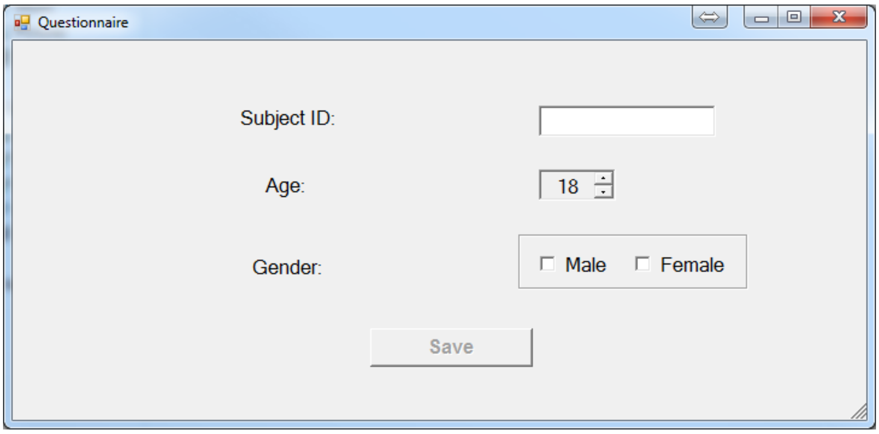
Congratulations! You know the characters well. Now it is the time to play the game…

Section C
Game Phase

Welcome to the main game! This game begins with a survey about some of your information. Then you can play with the characters in whatever way you find fun. Lastly, you can build your social network and play with them for friends or fortune, you choose!

Survey

Firstly, please fill in the survey. The information is strictly confidential, and will only be used for research purposes.



1. Please fill in your Subject ID as provided by the experimenter

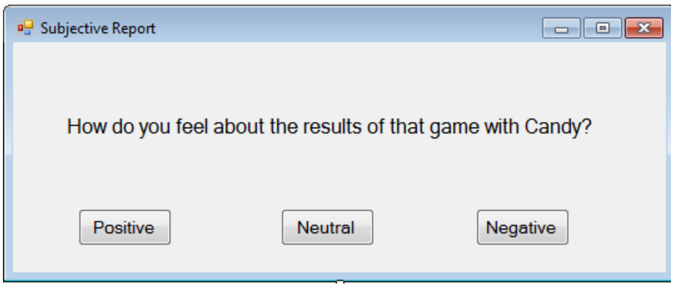
2. Please fill in your Age and your Gender in the corresponding boxes

3. Press the Save button then proceed to the game

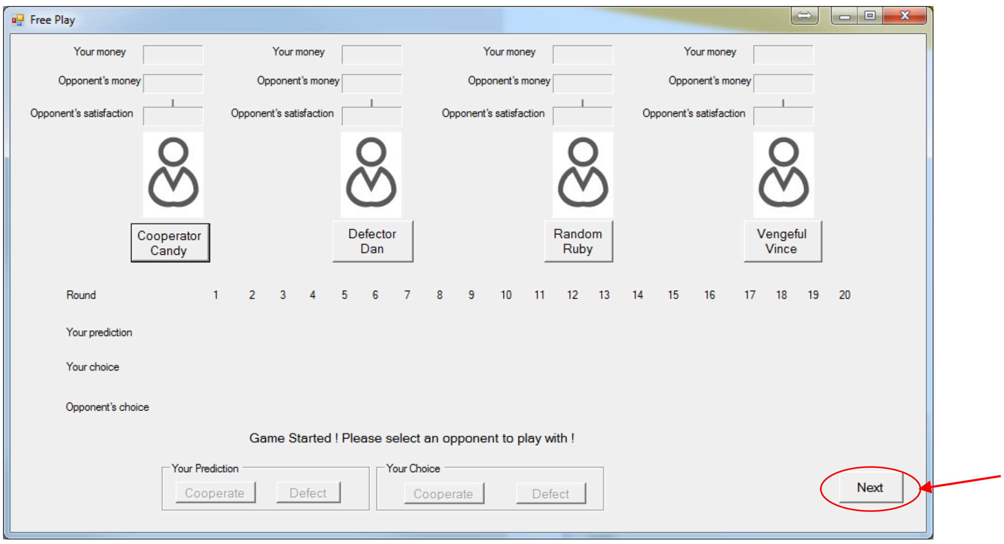
Now play with your characters and organise your own team, for friends or fortune, YOU CHOOSE!

Free play

1. Play with Cooperator Candy, Defector Dan, Random Ruby and Vengeful Vince individually.
2. Play with each character in whatever way you find fun, for friends or fortune.
3. After each character, please rate your emotion based on the results, choosing positive, neutral or negative…



4. When you finish playing with all characters, you can proceed to the social network session by pressing the Next button.



Social network

In the social network frame, you can build your own social network and play with them for friends or fortune, Let's start……

Team up

Build your own social network by choosing whoever you enjoy playing against.

Remember…

1. You may have all the same characters or a combination of different characters.

2. You can add less than eight characters into your social network, but no more than eight!

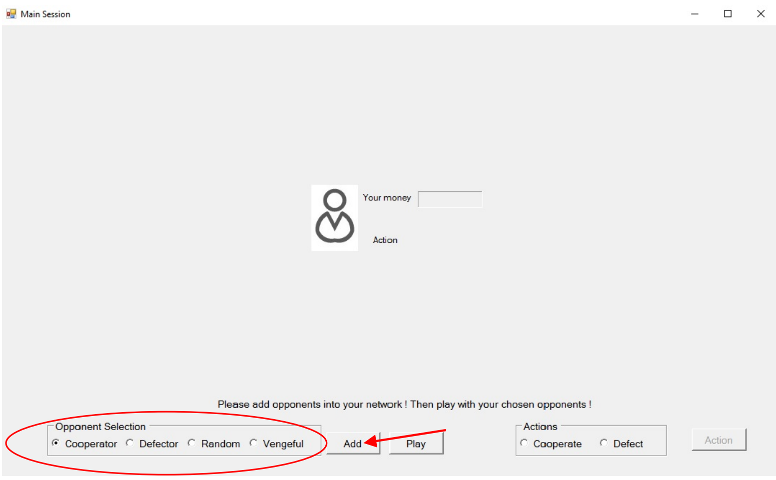
3. You won't make any more money by adding more characters but your network will be more satisfied.

4. you only have one chance to build your social network, and you won't be able to change your network after this.

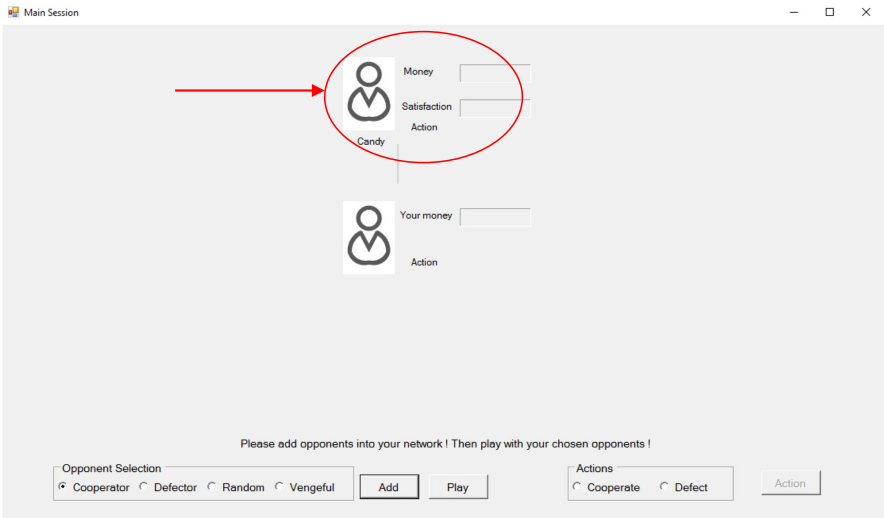
Now follow our instructions to build your network…

Add characters

1. **Click the radio button of your chosen character.**
2. **Click the Add button to incorporate the character in the network.**

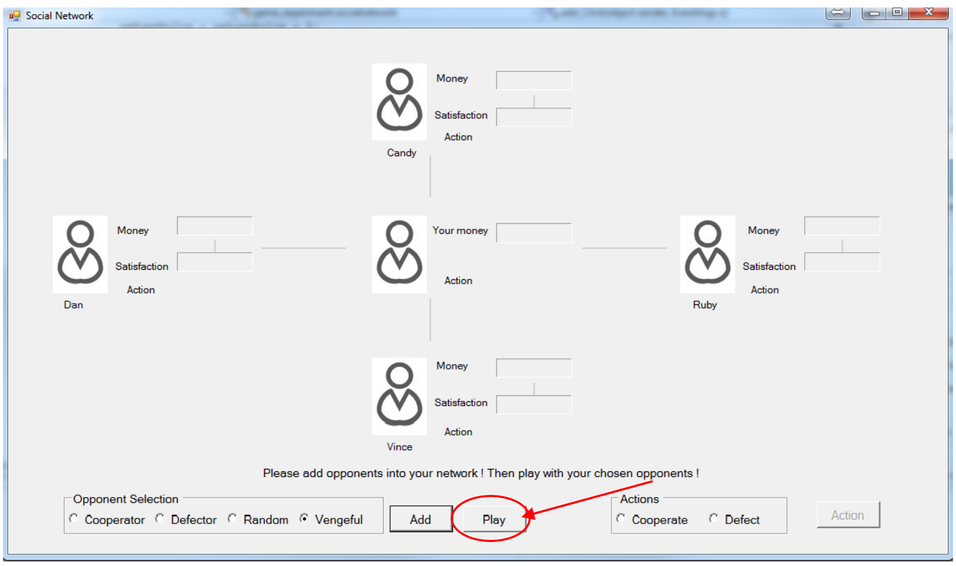


3. See your chosen characters in the interface



4. Repeat for as many (or as few) characters as you like (up to eight).

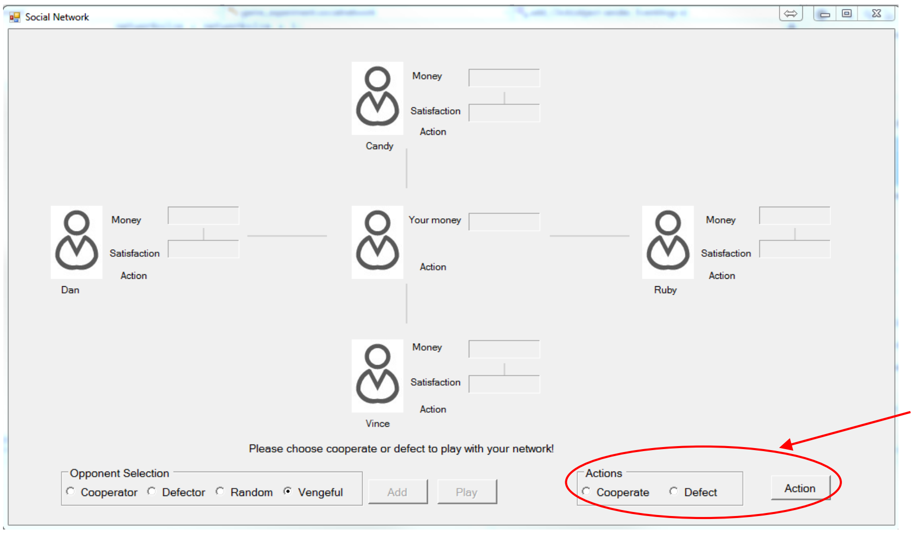
5. Press the **Play** button when you are done



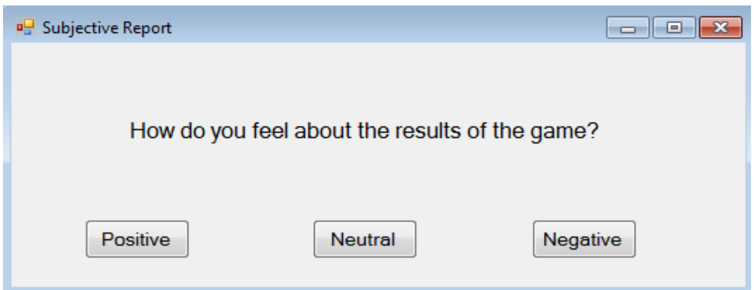
Play

When you have organised your social network, you can play with your network by choosing cooperate or defect in the Action Box.

Play in whatever way is fun, for friends or fortune, YOU CHOOSE!



Please rate your emotion before, during and after playing with your network.



Appendix B

An Experiment that Compares Classification Techniques

B.1 Aim

The aim of this experiment is to compare different classification techniques for identifying achievement, affiliation and power motivation. Four classifiers are compared in this experiment to classify motivation using gameplay behaviour and EEG data, and the best one is selected because of the highest accuracy.

B.2 Method

Four different classification methods (C4.5, KNN, RandomForest and nave bayes) were employed. C4.5 is a class for decision tree family [161]. The decision tree is a rule-based method. It predicts with a set of nested rules. At each decision node of the tree, it enters a branch according to the judgement result, and repeatedly performs such operations until it reaches the leaf node, and the decision result is obtained. These rules of the decision tree are obtained through training. The decision tree is a discriminant model and a nonlinear model, which naturally supports multi-class classification problems. In our analysis, the minimum number of instances in each leaf is 2. For pruning, the data are divided into three folders, one folder is for pruning, the rest is for growing the tree. The confidence factor used for pruning is 0.25, small value incurs more pruning. It also considered the subtree raising operation when pruning.

The Bayesian classifier is a branch of supervised learning method [162]. The feature vector x of the sample in the classification problem has a causal relationship with the type y of the sample. Since the sample belongs to the type y, it has a feature value x. The opposite is done by the classifier, which is to push back the category y to which the sample belongs under the condition that the feature vector of the known sample is x. According to Bayesian formula

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \tag{B.1}$$

As long as you know the probability distribution $p(x)$ of the feature vector, the probability $p(y)$ of each class, and the conditional probability $p(x|y)$ of each class of samples, you can calculate the probability that the sample belongs to each class $p(y|x)$. If you only need to determine the category, compare the probability that the sample belongs to each class, and find the one with the largest value. Therefore $p(x)$ can be ignored because it is the same for all classes. The discriminant function of the simplified classifier is

$$\arg\max_y p(x|y)p(y) \tag{B.2}$$

The training objective is to determine the parameters of $p(x|y)$, which is generally used for maximum likelihood estimation. The Bayesian classifier is a nonlinear model that naturally supports multi-classification problems. If the components of the sample feature vector are independent of each other, then it is called a naive Bayes classifier.

Random Forest is used for constructing a forest of random trees [163]. A random forest consists of multiple decision trees. The accuracy of the model can be improved by using multiple decision tree joint predictions. These decision trees are trained by constructing a sample set by randomly sampling the training sample set. Since the training sample set is constructed by random sampling, it is called a random forest. The random forest not only samples the training samples, but also randomly samples the components of the feature vector. When training the decision tree, only a part of the sampled feature components is used as candidate features for splitting each time. The number of trees to be generated is 100. For each random tree, the number of randomly chosen attributes is $log_2(number\ of\ attributes) + 1$.

The results discussed in chapter 5 use K-Nearest Neighbour (KNN) Classification [151]. KNN is a supervised machine-learning algorithm. When predicting a new sample, KNN finds the K most similar training samples (the nearest neighbours) and their corresponding labels. Then it takes a majority vote from the K nearest neighbours and sets the winning label as the class for the new sample. We chose KNN because it is a completely non-parametric approach that works well in situations where the decision boundary is highly non-linear. It is a computationally intensive method, but works well with small data sets. We select the value of K as 3 or 6 based on cross-validation results. Euclidean distance was used as the similarity function. Five-fold cross validation was chosen. This splits the whole dataset into five folds, each of which is used for training and testing. The nested cross-validation is not employed in the classification because it is more suitable for data-rich situations [164]. The mean accuracy and standard deviation were estimated over 10 runs of five-fold cross validation.

B.3 Results

Tab. B.1 shows classification accuracies for four different classifiers using gameplay behaviour from individual play phase. Random forest obtained the highest accuracy for achievement motivation classification. KNN has the best performance

Table B.1: Comparison of classification accuracies among different classifiers using player behaviour from IPP

Motivation	***Gameplay behaviour from individual play phase***				
	J48	*KNN*	*Random forest*	*Nave bayes*	*SVM*
Achievement	36%±22%	43%±20%	38%±20%	30%±20%	52%±10%
Affiliation	49%±18%	62%±20%	57%±19%	52%±22%	52%±12%
Power	39%±20%	42%±21%	49%±22%	38%±19%	49%±11%

Table B.2: Comparison of classification accuracies among different classifiers using EEG signal from IPP

Motivation	***EEG signal from individual play phase***				
	J48	*KNN*	*Random forest*	*Nave bayes*	*SVM*
Achievement	58%±19%	65%±21%	87%±24%	72%±30%	52%±10%
Affiliation	37%±18%	76%±17%	35%±20%	42%±17%	52%±12%
Power	60%±22%	73%±19%	72%±16%	67%±17%	49%±11%

for affiliation and power motivation classification.

Tab .B.2 shows classification accuracies among different classifiers using EEG signals from individual play phase. KNN achieve the best classification performance for affiliation and power motivation. As for achievement motivation classification, J48 has the best performance.

Tab.B.3 shows the classification results using gameplay behaviour from social network phase. KNN achieved the best performance for affiliation and power motivation classification. While random forest has the best performance for achievement motivation.

Tab. B.4 shows that KNN has the best performance for power motivation, that random forest achieves the best performance for affiliation motivation, and that J48 has the best performance for achievement motivation.

Table B.3: Comparison of classification accuracies among different classifiers using player behaviour from SNP

Motivation	***Gameplay behaviour from social network phase***				
	J48	*KNN*	*Random forest*	*Nave bayes*	*SVM*
Achievement	40%±18%	38%±20%	35%±17%	36%±17%	52%±10%
Affiliation	59%±22%	60%±19%	70%±16%	68%±22%	53%±12%
Power	35%±16%	37%±17%	33%±16%	34%±19%	49%±11%

Table B.4: Comparison of classification accuracies among different classifiers using EEG data from SNP

Motivation	***EEG signal from social network phase***				
	J48	*KNN*	*Random forest*	*Nave bayes*	*SVM*
Achievement	76%±18%	66%±17%	76%±15%	52%±21%	57%±13%
Affiliation	53%±17%	32%±18%	74%±14%	72%±20%	53%±12%
Power	62%±24%	68%±16%	55%±20%	51%±23%	75%±15%

B.4 Summary

From results using four different classifiers, we conclude that KNN generally achieves the best performance for player motive classification. This is supported both from gameplay behaviour and EEG data in individual play and social network phase.

Appendix C

An Experiment that Compares Artifact Removal Techniques

C.1 Aim

The aim of this experiment is to compare three different artifact removal techniques and to decide which one gives the optimal EEG signals for further data analysis. The optimal artifact removal technique is selected based on the classification accuracies.

C.2 Method

Fully automated statistical thresholding for EEG artifact rejection (FASTER) is an automatic artifact removal technique [165]. In this method, five aspects of EEG data (channels, epochs, ICs, single-channel single epochs, and aggregated data) are analysed for artifact removal. Parameters are estimated both from the EEG time series and from the independent components of EEG data; outliers are extracted and removed. FASTER deals with contaminated channels, eye movement, EMG artifact, linear trends and white noise.

An automatic EEG artifact detector based on the joint use of spatial and temporal features (ADJUST) is another automatic artifact removal algorithm [153]. This method analyses EEG independent components after doing independent component analysis (ICA). Artifact-related independent components are identified depending on their temporal course and spatial distribution. It not only relies on a single feature, but utilises feature combination to do the job efficiently and systematically. Eye blinks, horizontal eye movement, vertical eye movement and generic discontinuous are considered in this technique.

We proposed a manual artifact selection method to tackle ocular artifacts (eye blinks, eye movement). The observation here is subjects have individual characteristics of EEG artifact, which we call individual EEG artifact signatures. The procedure is as follows.

- Step 1: Extract the artifact from subjects EEG recordings individually.
- Step 2: Calculate the mean of the artifact as the individual EEG artifact signatures.
- Step 3: Subtract the individual EEG artifact from the EEG recordings to obtain the clean EEG signals.
- Step 4: Evaluate the artifact removal methods by looking at the metrics (classification performance, etc.) before and after the use of the method.

The three artifact removal techniques are compared when performing motivation classification. We chose K-nearest neighbours (KNN) to do the H-L, L-H and other classification. The accuracies of each motivation in individual play and social network phase were presented.

Table C.1: Performance of Motivation classification using three different artifact removal technique

Artifact removal	***EEG signals from individual play phase***		
	Achievement	*Affiliation*	*Power*
FASTER	65%±18%	45%±20%	70%±20%
ADJUST	65%±21%	76%±17%	73%±18%
Manual	73%±25%	54%±22%	52%±21%

C.3 Results

Tab. C.1 shows the performance of three artifact removal techniques on motivation classification. We can see that the manual artifact removal method achieved the best accuracy for achievement motivation classification, ADJUST had the best performance for affiliation and power motivation classification. For affiliation and power motivation, manual artifact removal only achieved accuracies of around 50%. FASTER method has only 45% accuracy for affiliation motivation. Thus, it can be observed that ADJUST performed the most reliably among achievement, affiliation and power motivation. Furthermore, by visually inspecting the raw EEG signal, we observed the ocular artifact in the EEG recording, which can be effectively detected and removed by the ADJUST artifact removal technique.

C.4 Summary

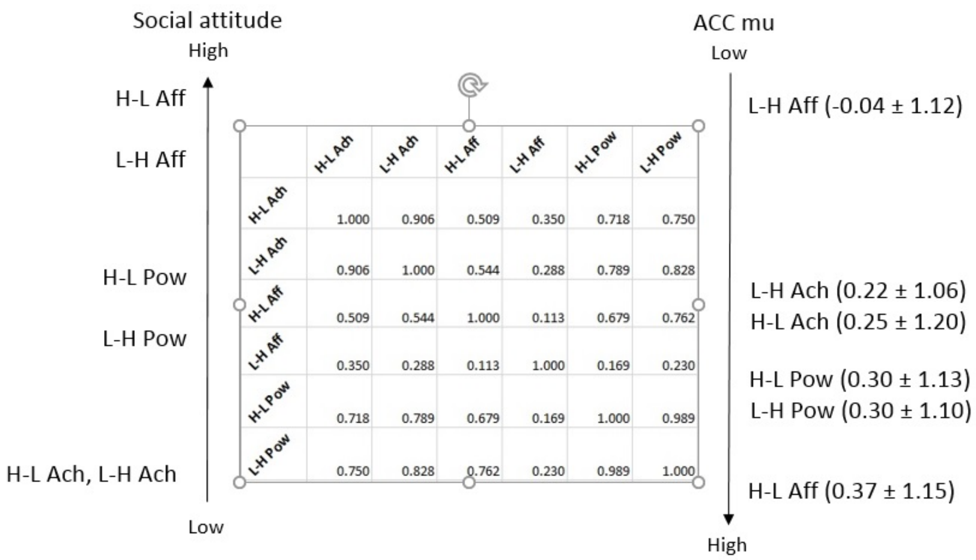
According to the results obtained from using three artifact removal techniques for player motivation classification, as well as the visual inspection of EEG signals, we conclude that ADJUST is the optimal choice for artifact removal.

Appendix D

Numerical Results Supporting NPC Design

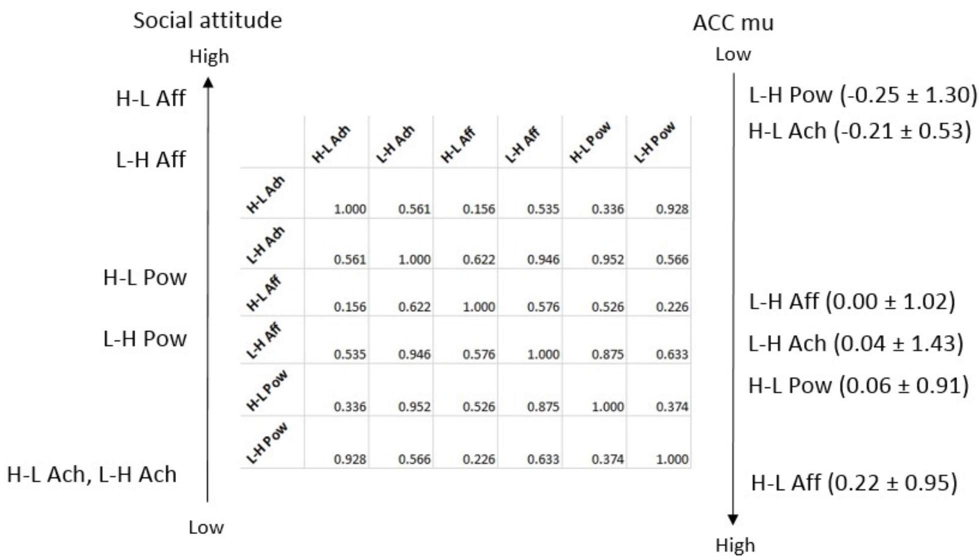
D.1 Introduction

This section presents the numerical evidence that supports the summary of using NPCs to predict risk-taking and social attitudes as described in Section 6.3, Chapter 6. We analyse EEG features to identify the effectiveness of individual NPC for assessing risk-taking and social attitudes. It is performed based on EEG signals collected from each trial in IPP, players' actions, money and satisfaction feedback.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.906	0.509	0.350	0.718	0.750
L-H Ach	0.906	1.000	0.544	0.288	0.789	0.828
H-L Aff	0.509	0.544	1.000	0.113	0.679	0.762
L-H Aff	0.350	0.288	0.113	1.000	0.169	0.230
H-L Pow	0.718	0.789	0.679	0.169	1.000	0.989
L-H Pow	0.750	0.828	0.762	0.230	0.989	1.000

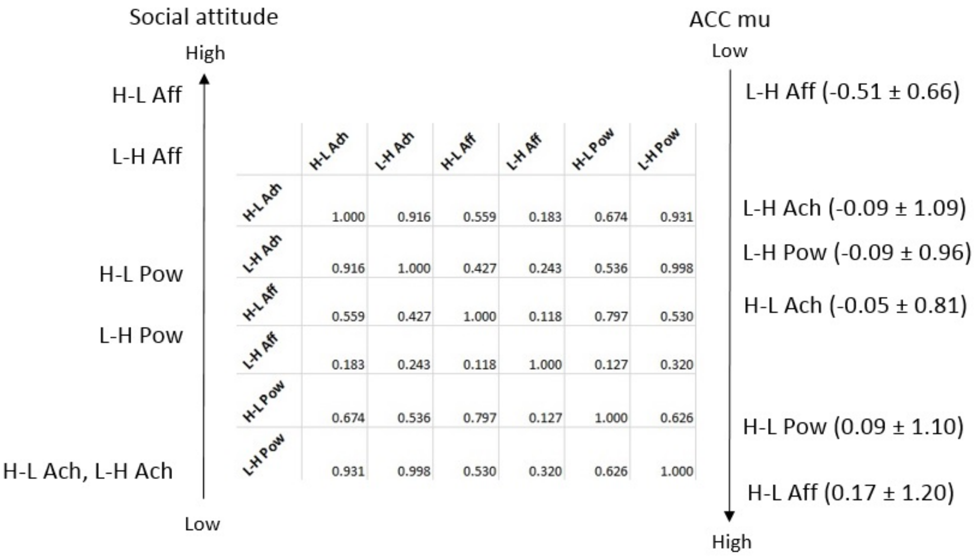
(a) IPP



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.561	0.156	0.535	0.336	0.928
L-H Ach	0.561	1.000	0.622	0.946	0.952	0.566
H-L Aff	0.156	0.622	1.000	0.576	0.526	0.226
L-H Aff	0.535	0.946	0.576	1.000	0.875	0.633
H-L Pow	0.336	0.952	0.526	0.875	1.000	0.374
L-H Pow	0.928	0.566	0.226	0.633	0.374	1.000

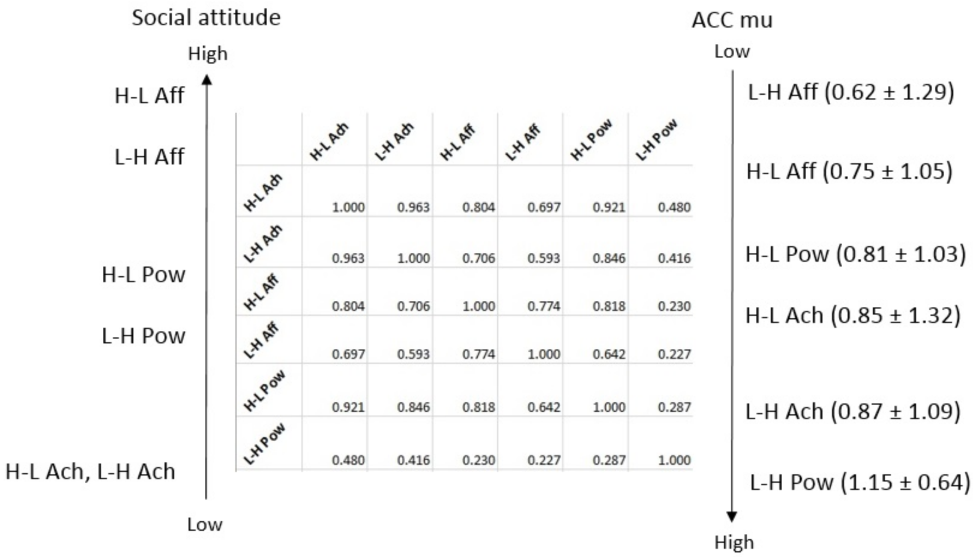
(b) Action

Figure D.1: Results of using ACC mu band in IPP and action to reveal social attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.916	0.559	0.183	0.674	0.931
L-H Ach	0.916	1.000	0.427	0.243	0.536	0.998
H-L Aff	0.559	0.427	1.000	0.118	0.797	0.530
L-H Aff	0.183	0.243	0.118	1.000	0.127	0.320
H-L Pow	0.674	0.536	0.797	0.127	1.000	0.626
L-H Pow	0.931	0.998	0.530	0.320	0.626	1.000

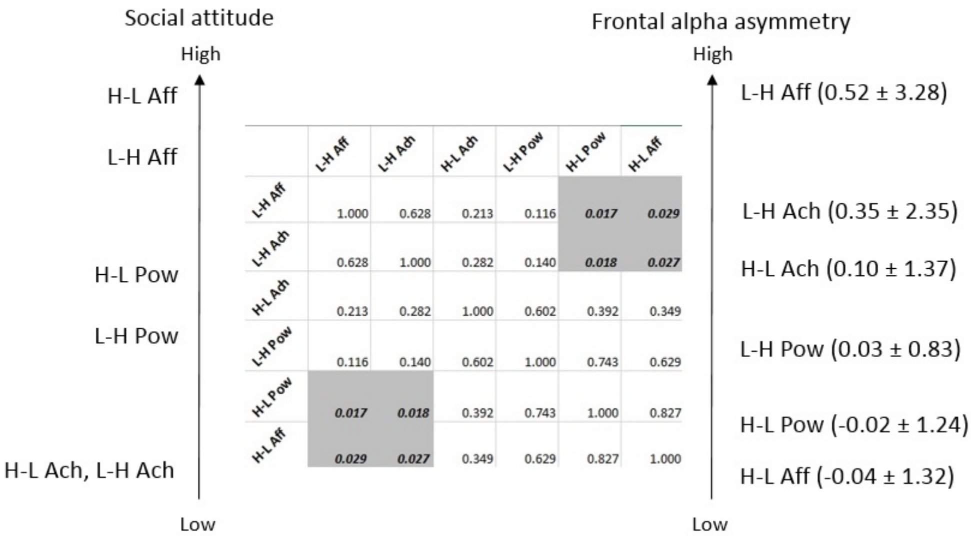
(a) Money feedback



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.963	0.804	0.697	0.921	0.480
L-H Ach	0.963	1.000	0.706	0.593	0.846	0.416
H-L Aff	0.804	0.706	1.000	0.774	0.818	0.230
L-H Aff	0.697	0.593	0.774	1.000	0.642	0.227
H-L Pow	0.921	0.846	0.818	0.642	1.000	0.287
L-H Pow	0.480	0.416	0.230	0.227	0.287	1.000

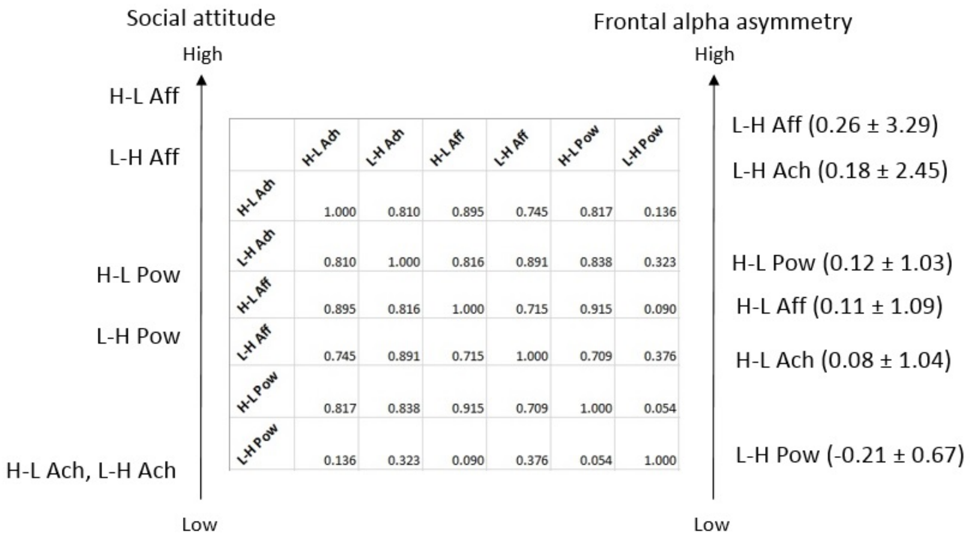
(b) Satisfaction feedback

Figure D.2: Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	H-L Ach	L-H Pow	H-L Pow	H-L Aff
L-H Aff	1.000	0.628	0.213	0.116	*0.017*	*0.029*
L-H Ach	0.628	1.000	0.282	0.140	*0.018*	*0.027*
H-L Ach	0.213	0.282	1.000	0.602	0.392	0.349
L-H Pow	0.116	0.140	0.602	1.000	0.743	0.629
H-L Pow	*0.017*	*0.018*	0.392	0.743	1.000	0.827
H-L Aff	*0.029*	*0.027*	0.349	0.629	0.827	1.000

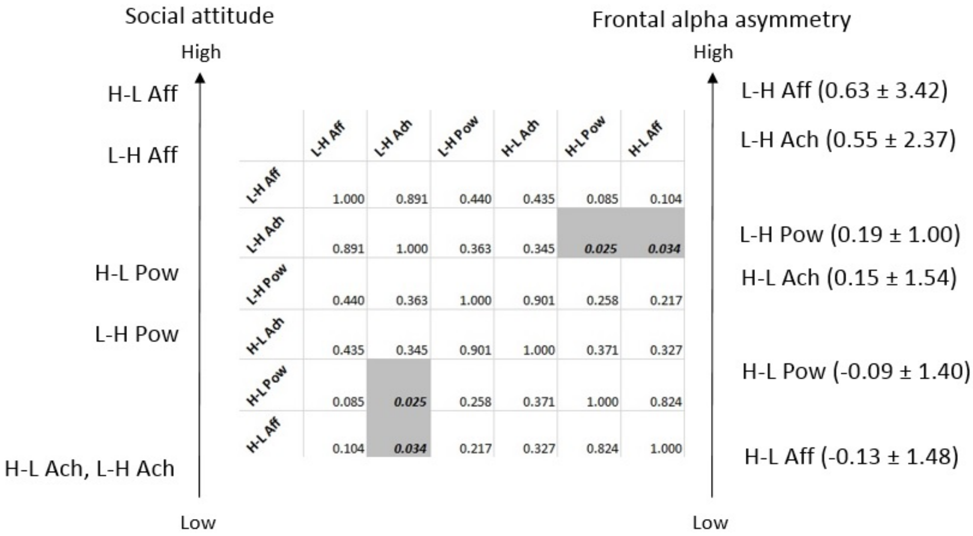
(a) IPP



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.810	0.895	0.745	0.817	0.136
L-H Ach	0.810	1.000	0.816	0.891	0.838	0.323
H-L Aff	0.895	0.816	1.000	0.715	0.915	0.090
L-H Aff	0.745	0.891	0.715	1.000	0.709	0.376
H-L Pow	0.817	0.838	0.915	0.709	1.000	0.054
L-H Pow	0.136	0.323	0.090	0.376	0.054	1.000

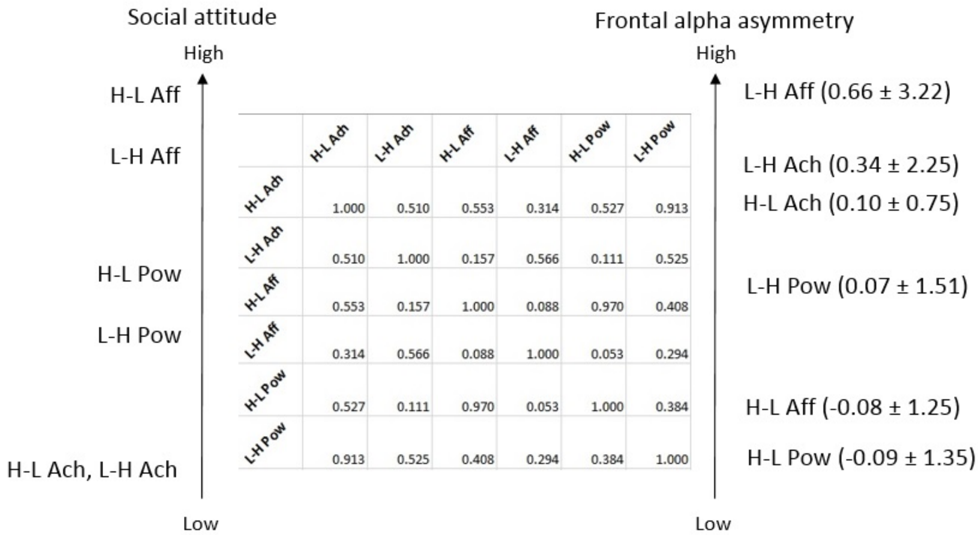
(b) Action

Figure D.3: Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	L-H Pow	H-L Ach	H-L Pow	H-L Aff
L-H Aff	1.000	0.891	0.440	0.435	0.085	0.104
L-H Ach	0.891	1.000	0.363	0.345	***0.025***	***0.034***
L-H Pow	0.440	0.363	1.000	0.901	0.258	0.217
H-L Ach	0.435	0.345	0.901	1.000	0.371	0.327
H-L Pow	0.085	***0.025***	0.258	0.371	1.000	0.824
H-L Aff	0.104	***0.034***	0.217	0.327	0.824	1.000

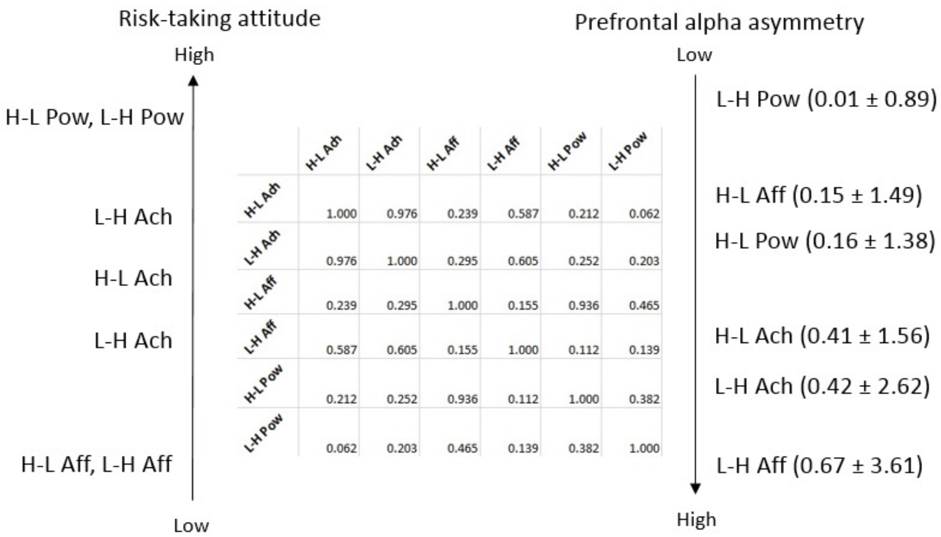
(a) Money feedback



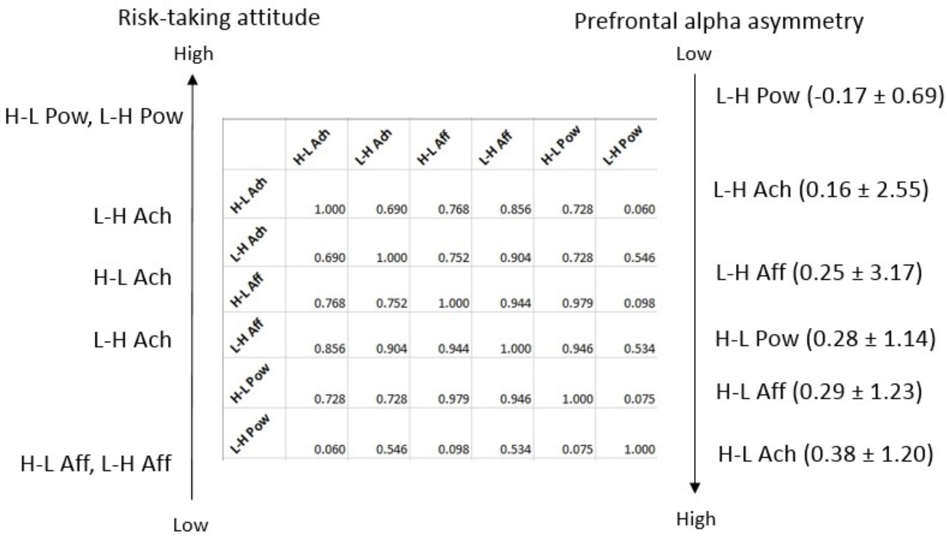
	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.510	0.553	0.314	0.527	0.913
L-H Ach	0.510	1.000	0.157	0.566	0.111	0.525
H-L Aff	0.553	0.157	1.000	0.088	0.970	0.408
L-H Aff	0.314	0.566	0.088	1.000	0.053	0.294
H-L Pow	0.527	0.111	0.970	0.053	1.000	0.384
L-H Pow	0.913	0.525	0.408	0.294	0.384	1.000

(b) Satisfaction feedback

Figure D.4: Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

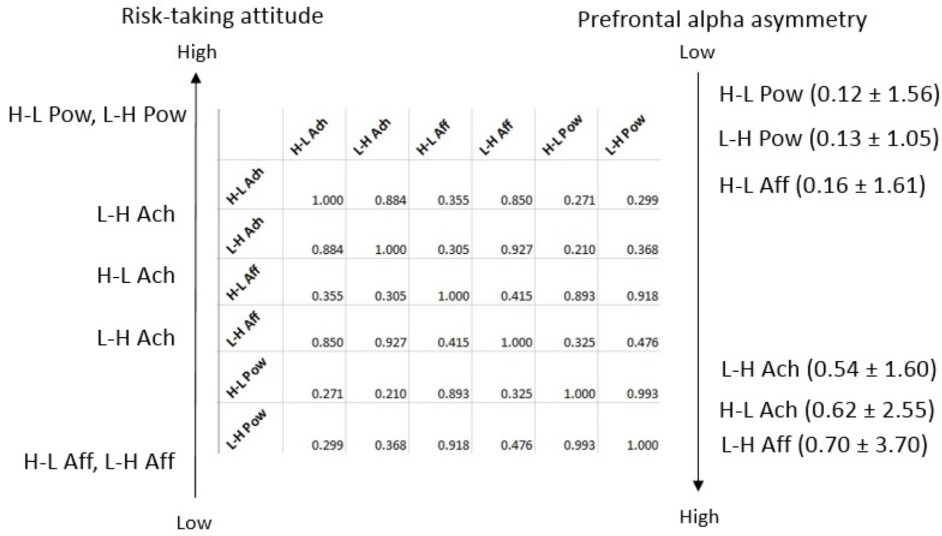


(a) IPP

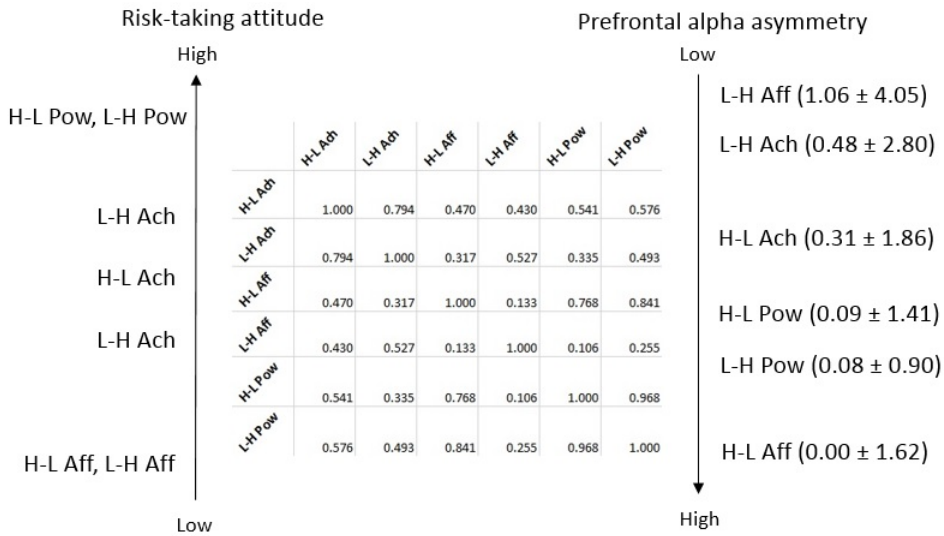


(b) Action

Figure D.5: Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

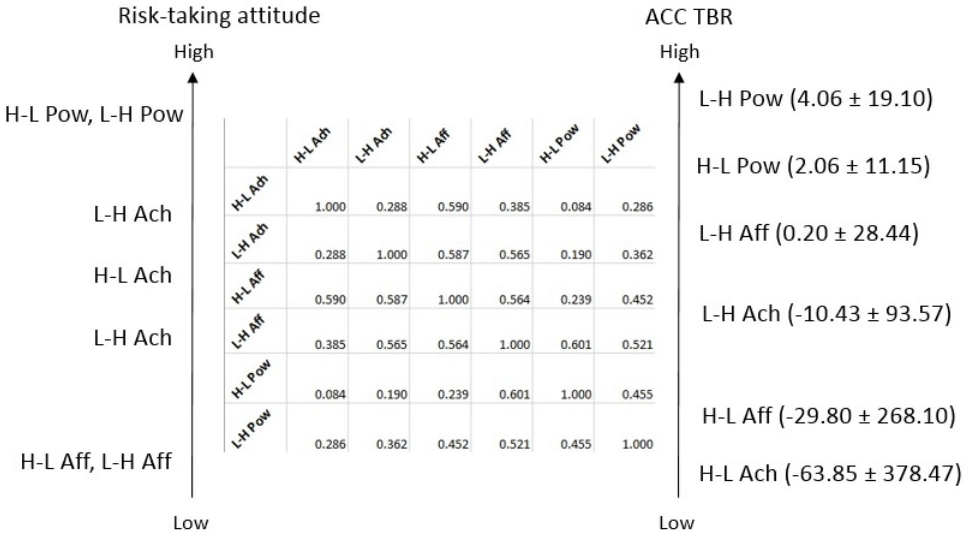


(a) Money feedback

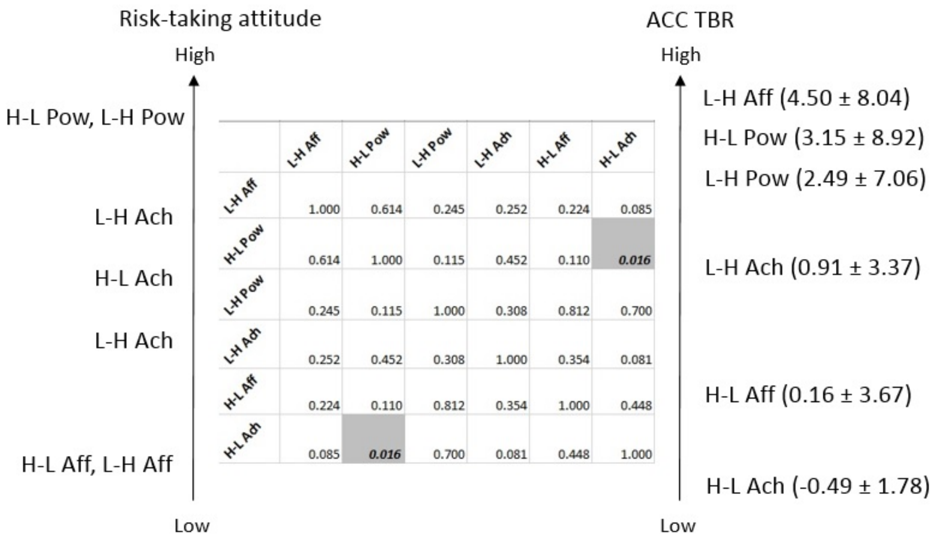


(b) Satisfaction feedback

Figure D.6: Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

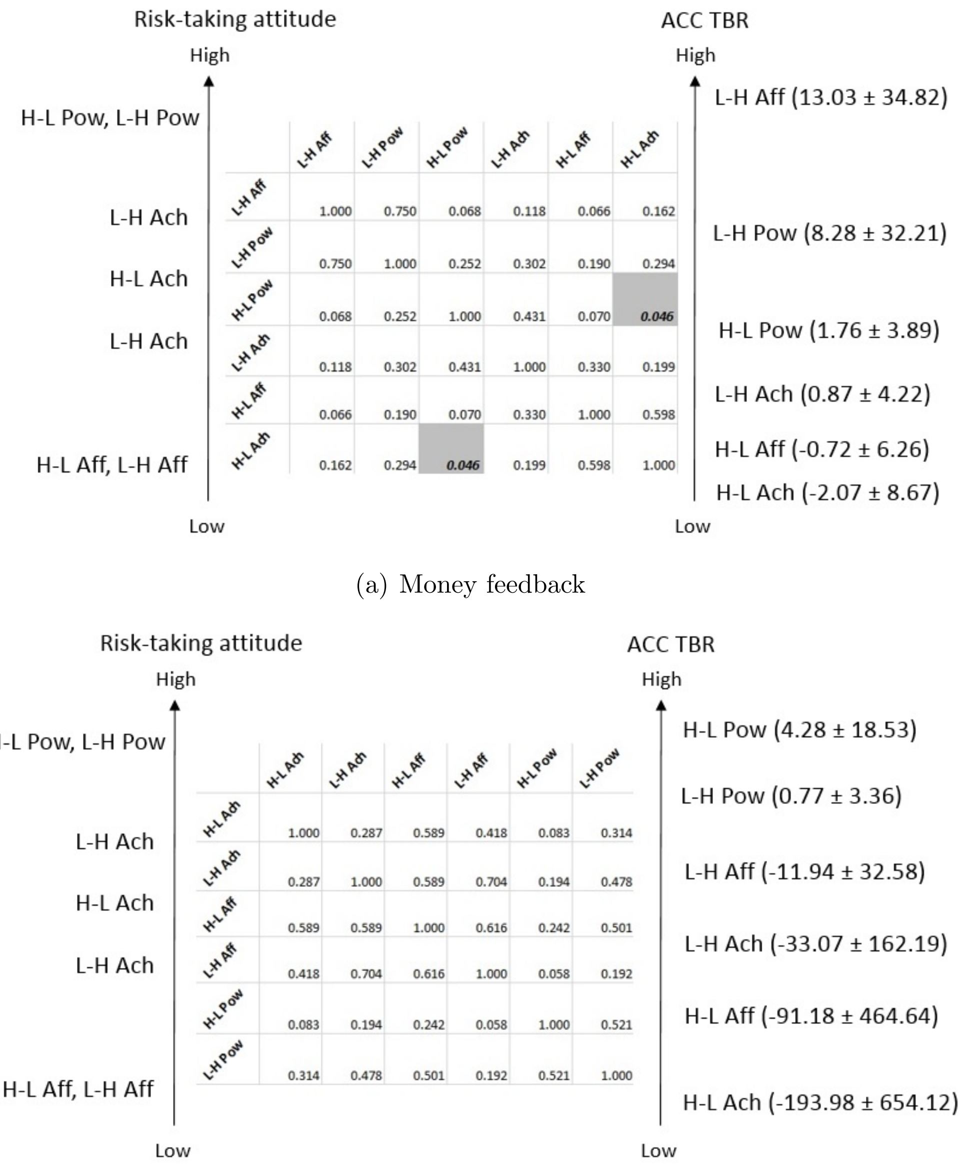


(a) IPP



(b) Action

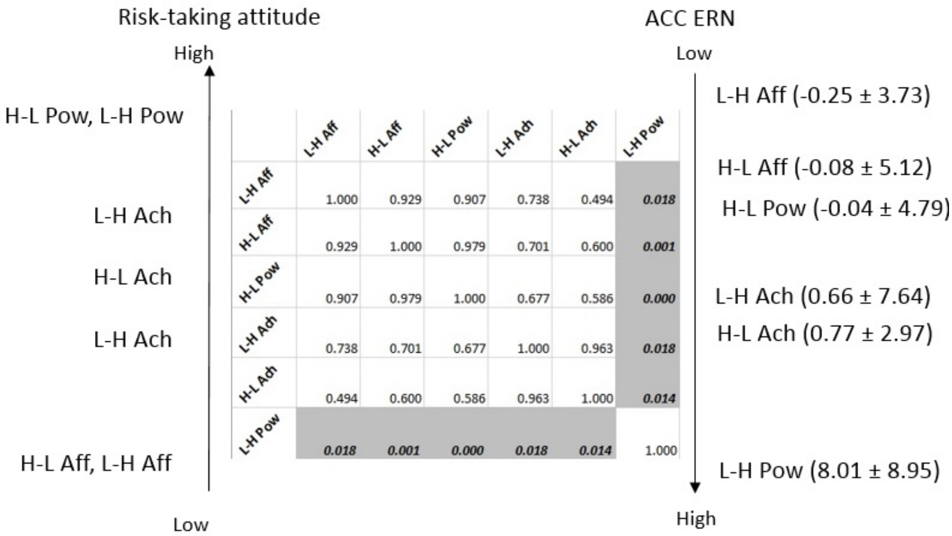
Figure D.7: Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



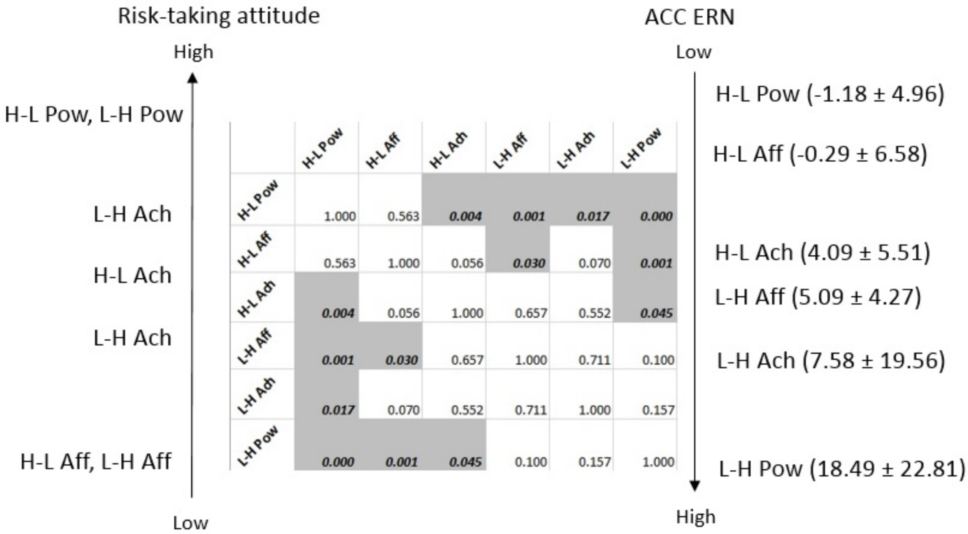
(a) Money feedback

(b) Satisfaction feedback

Figure D.8: Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

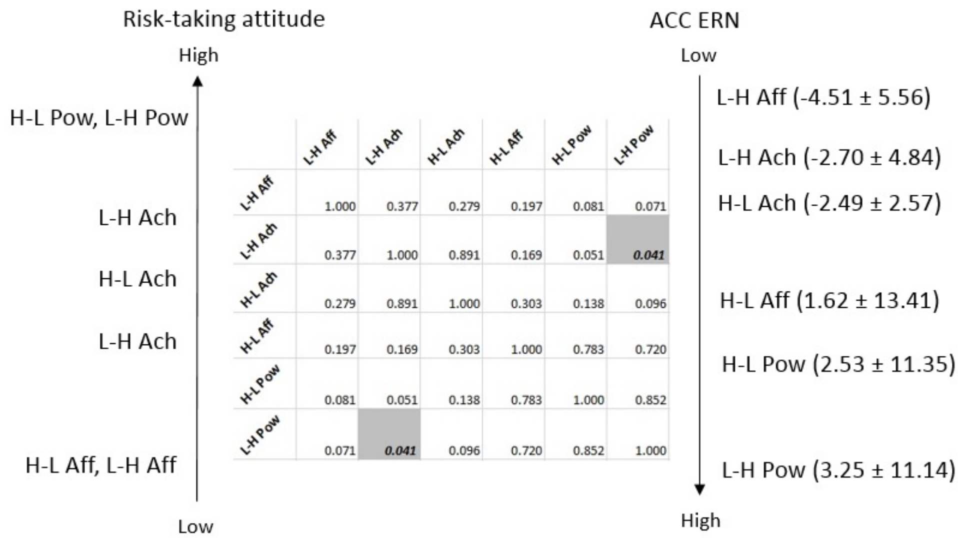


(a) IPP



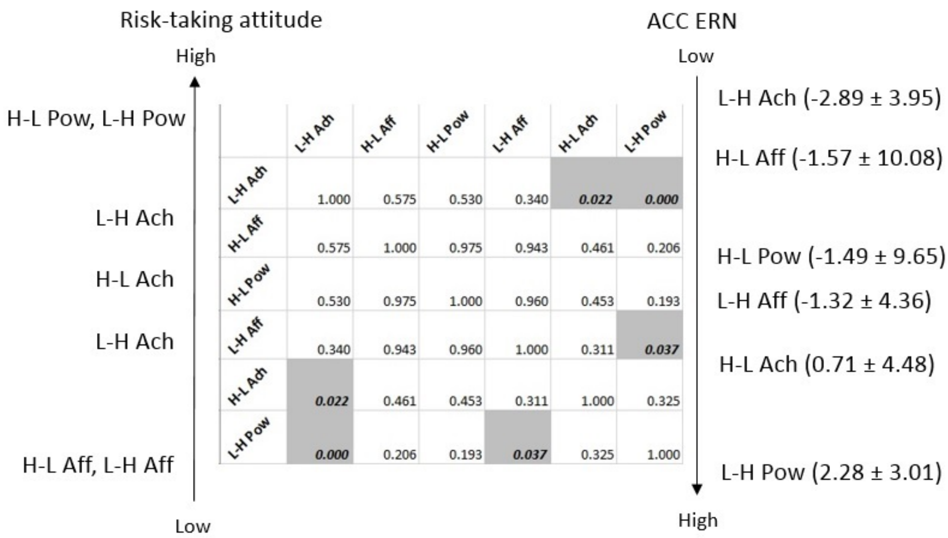
(b) Action

Figure D.9: Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	H-L Ach	H-L Aff	H-L Pow	L-H Pow
L-H Aff	1.000	0.377	0.279	0.197	0.081	0.071
L-H Ach	0.377	1.000	0.891	0.169	0.051	***0.041***
H-L Ach	0.279	0.891	1.000	0.303	0.138	0.096
H-L Aff	0.197	0.169	0.303	1.000	0.783	0.720
H-L Pow	0.081	0.051	0.138	0.783	1.000	0.852
L-H Pow	0.071	***0.041***	0.096	0.720	0.852	1.000

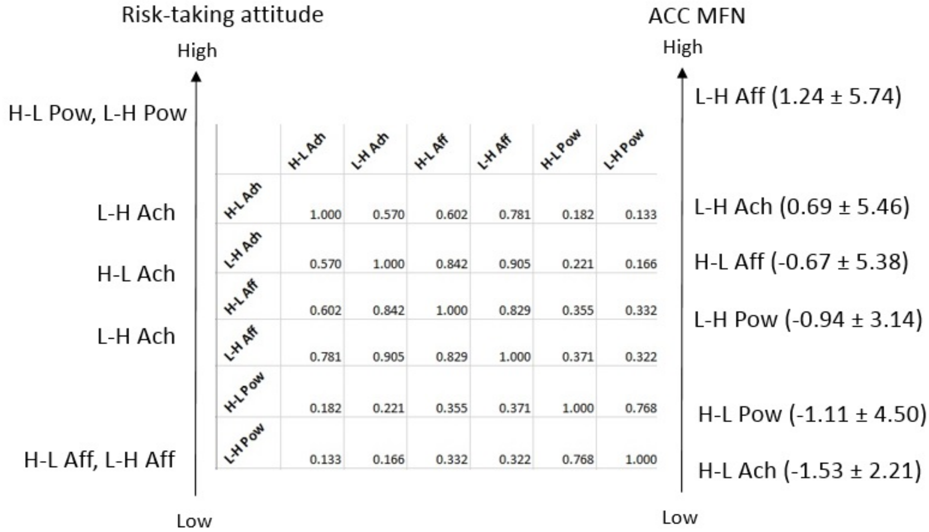
(a) Money feedback



	L-H Ach	H-L Aff	H-L Pow	L-H Aff	H-L Ach	L-H Pow
L-H Ach	1.000	0.575	0.530	0.340	***0.022***	***0.000***
H-L Aff	0.575	1.000	0.975	0.943	0.461	0.206
H-L Pow	0.530	0.975	1.000	0.960	0.453	0.193
L-H Aff	0.340	0.943	0.960	1.000	0.311	***0.037***
H-L Ach	***0.022***	0.461	0.453	0.311	1.000	0.325
L-H Pow	***0.000***	0.206	0.193	***0.037***	0.325	1.000

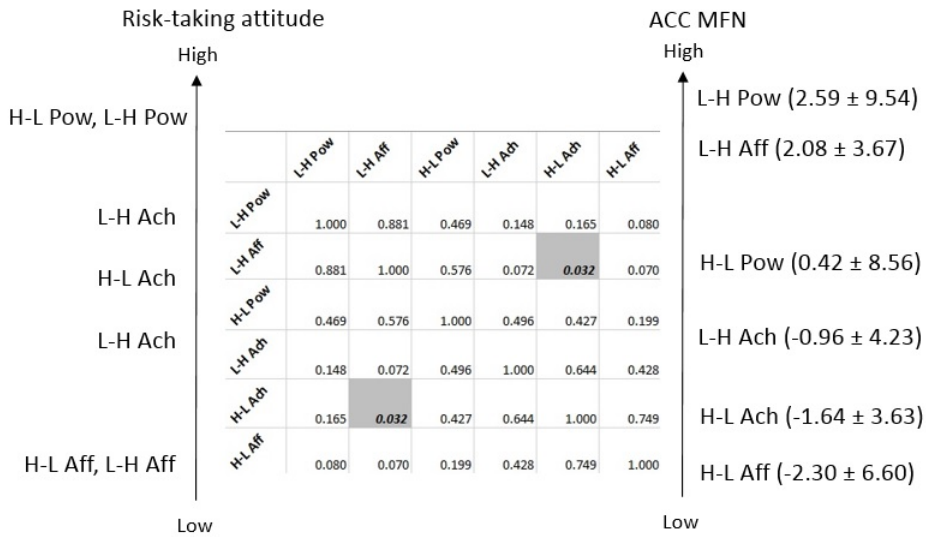
(b) Satisfaction feedback

Figure D.10: Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.570	0.602	0.781	0.182	0.133
L-H Ach	0.570	1.000	0.842	0.905	0.221	0.166
H-L Aff	0.602	0.842	1.000	0.829	0.355	0.332
L-H Aff	0.781	0.905	0.829	1.000	0.371	0.322
H-L Pow	0.182	0.221	0.355	0.371	1.000	0.768
L-H Pow	0.133	0.166	0.332	0.322	0.768	1.000

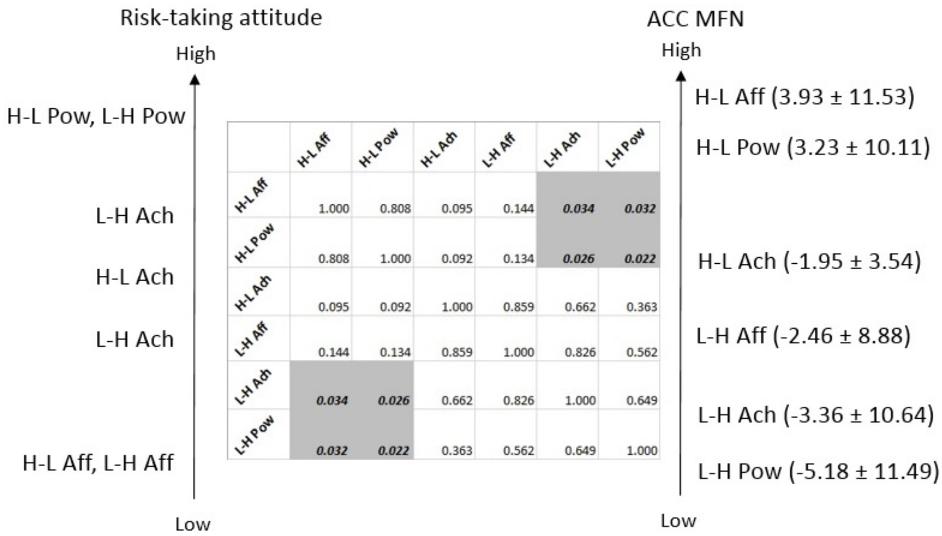
(a) IPP



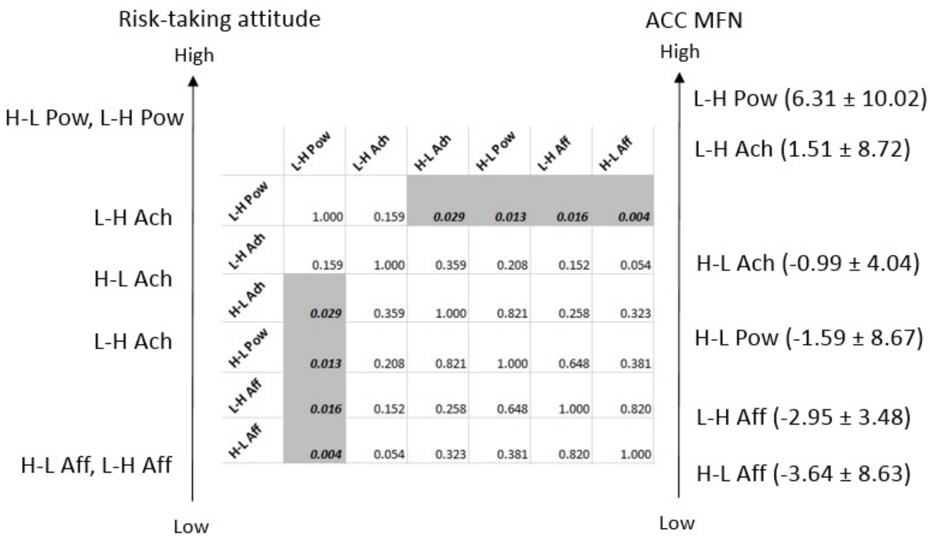
	L-H Pow	L-H Aff	H-L Pow	L-H Ach	H-L Ach	H-L Aff
L-H Pow	1.000	0.881	0.469	0.148	0.165	0.080
L-H Aff	0.881	1.000	0.576	0.072	***0.032***	0.070
H-L Pow	0.469	0.576	1.000	0.496	0.427	0.199
L-H Ach	0.148	0.072	0.496	1.000	0.644	0.428
H-L Ach	0.165	***0.032***	0.427	0.644	1.000	0.749
H-L Aff	0.080	0.070	0.199	0.428	0.749	1.000

(b) Action

Figure D.11: Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

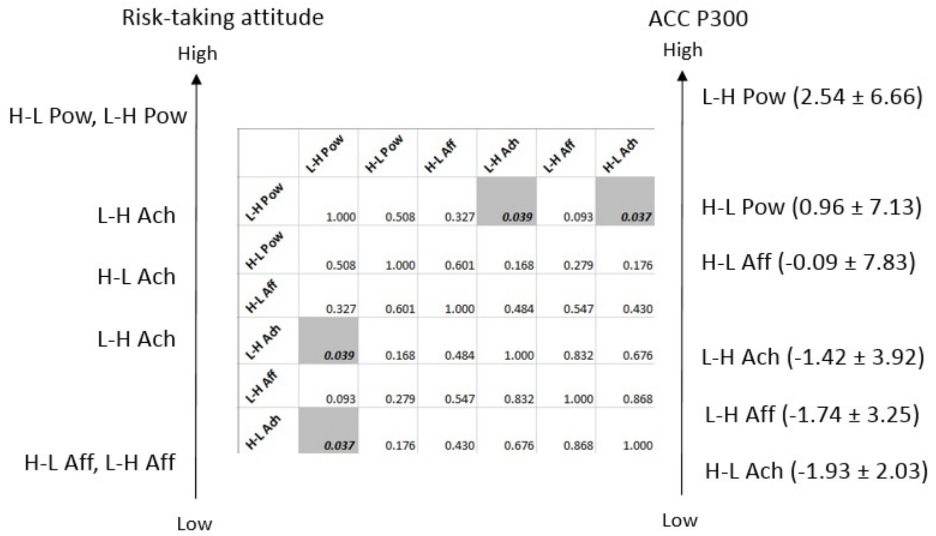


(a) Money feedback

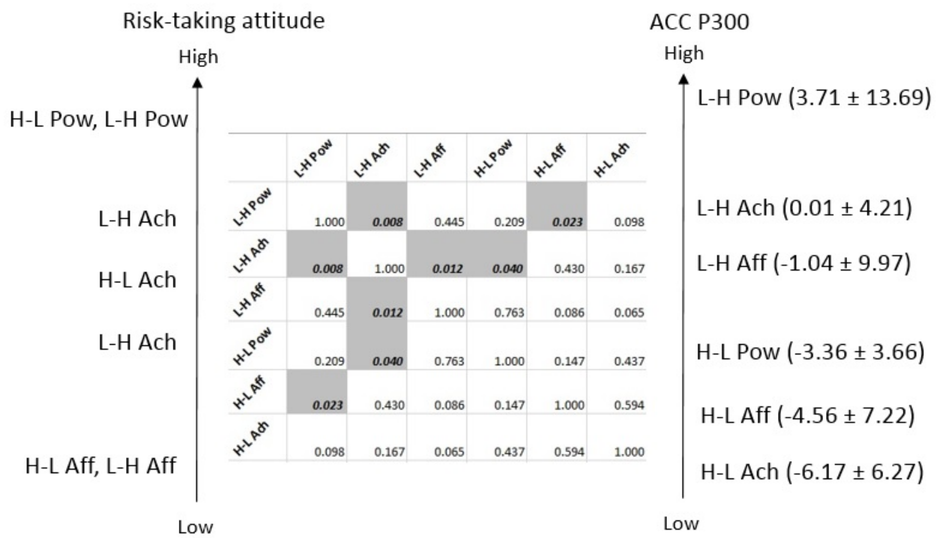


(b) Satisfaction feedback

Figure D.12: Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

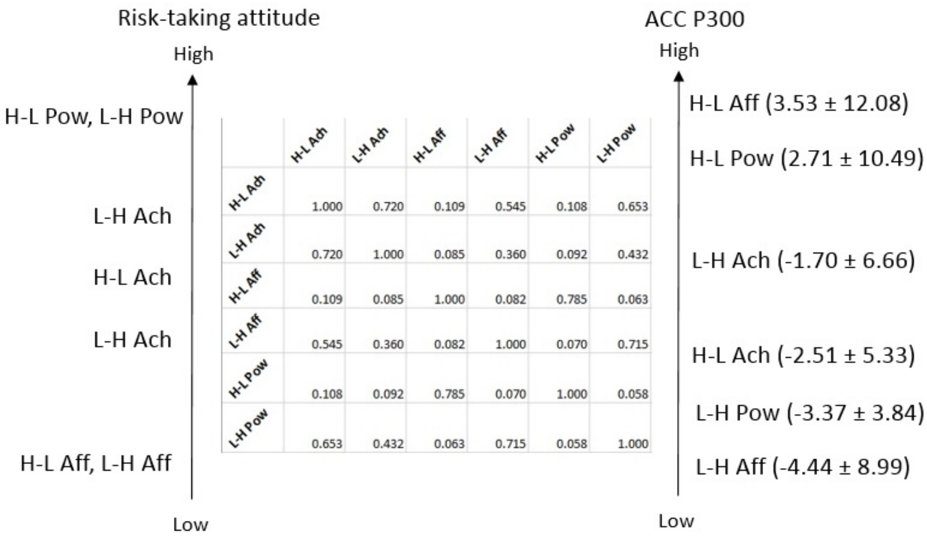


(a) IPP

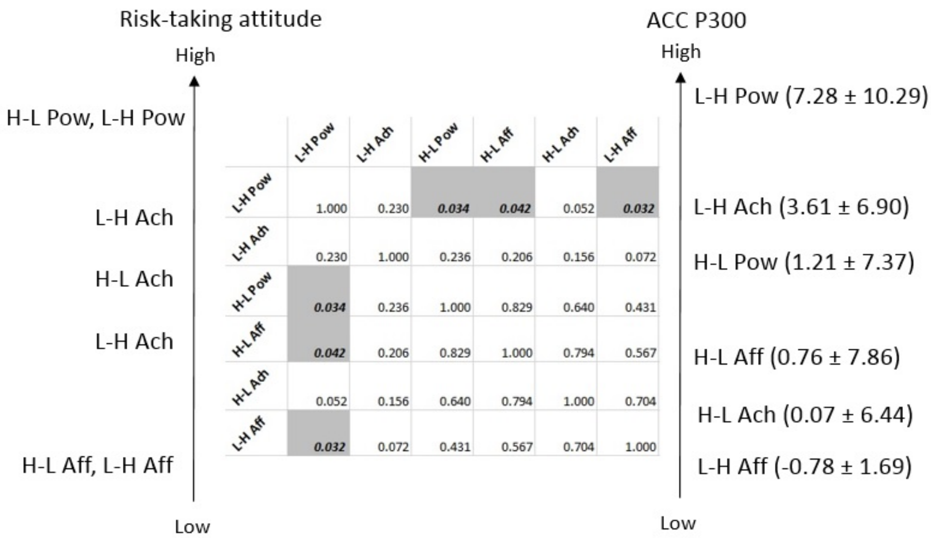


(b) Action

Figure D.13: Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.

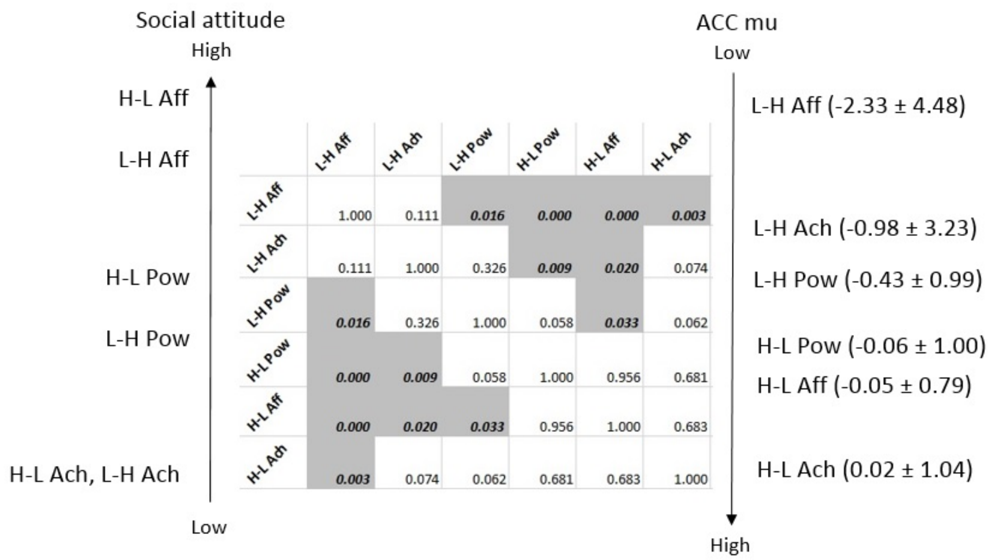


(a) Money feedback



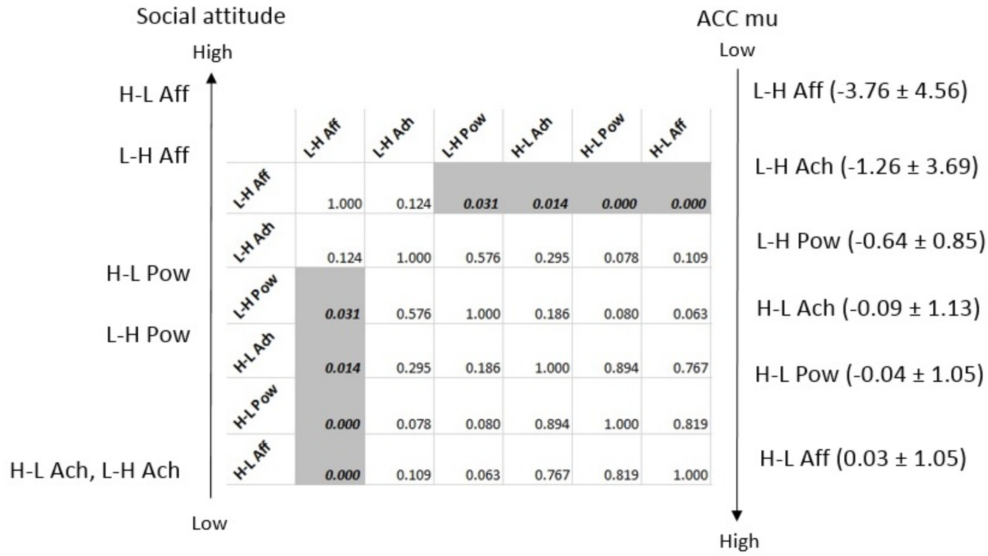
(b) Satisfaction feedback

Figure D.14: Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Cooperator Candy. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	L-H Pow	H-L Pow	H-L Aff	H-L Ach
L-H Aff	1.000	0.111	***0.016***	***0.000***	***0.000***	***0.003***
L-H Ach	0.111	1.000	0.326	***0.009***	***0.020***	0.074
L-H Pow	***0.016***	0.326	1.000	0.058	***0.033***	0.062
H-L Pow	***0.000***	***0.009***	0.058	1.000	0.956	0.681
H-L Aff	***0.000***	***0.020***	***0.033***	0.956	1.000	0.683
H-L Ach	***0.003***	0.074	0.062	0.681	0.683	1.000

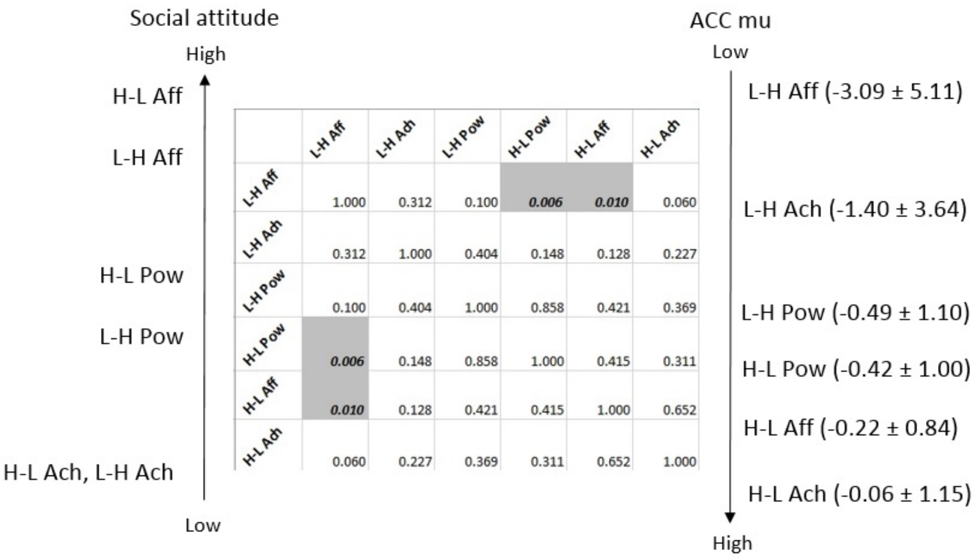
(a) IPP



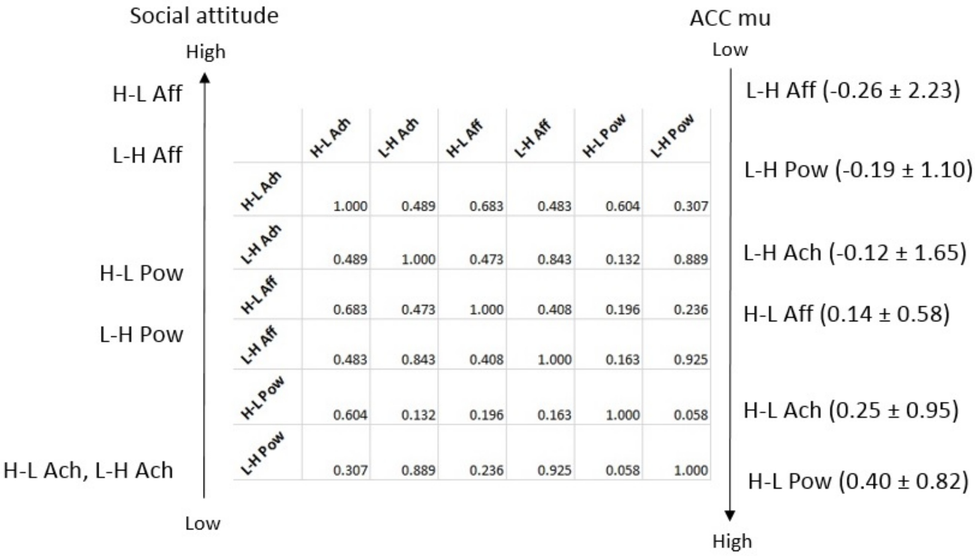
	L-H Aff	L-H Ach	L-H Pow	H-L Ach	H-L Pow	H-L Aff
L-H Aff	1.000	0.124	***0.031***	***0.014***	***0.000***	***0.000***
L-H Ach	0.124	1.000	0.576	0.295	0.078	0.109
L-H Pow	***0.031***	0.576	1.000	0.186	0.080	0.063
H-L Ach	***0.014***	0.295	0.186	1.000	0.894	0.767
H-L Pow	***0.000***	0.078	0.080	0.894	1.000	0.819
H-L Aff	***0.000***	0.109	0.063	0.767	0.819	1.000

(b) Action

Figure D.15: Results of using ACC mu band in IPP and action to reveal social attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

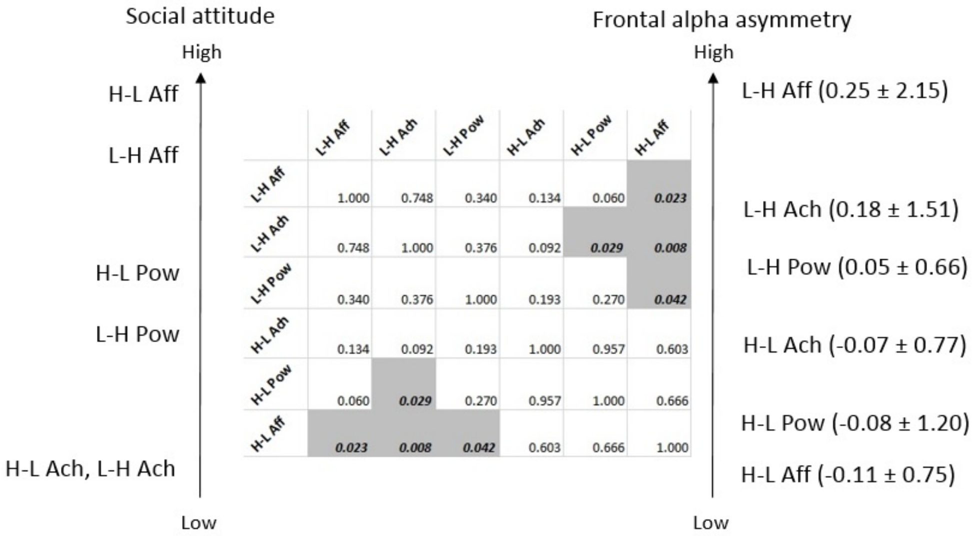


(a) Money feedback



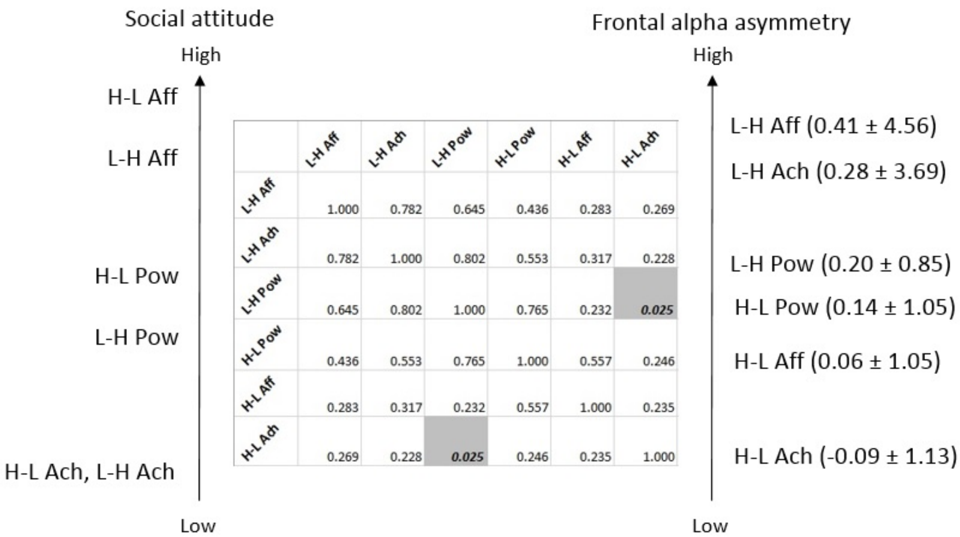
(b) Satisfaction feedback

Figure D.16: Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	L-H Pow	H-L Ach	H-L Pow	H-L Aff
L-H Aff	1.000	0.748	0.340	0.134	0.060	***0.023***
L-H Ach	0.748	1.000	0.376	0.092	***0.029***	***0.008***
L-H Pow	0.340	0.376	1.000	0.193	0.270	***0.042***
H-L Ach	0.134	0.092	0.193	1.000	0.957	0.603
H-L Pow	0.060	***0.029***	0.270	0.957	1.000	0.666
H-L Aff	***0.023***	***0.008***	***0.042***	0.603	0.666	1.000

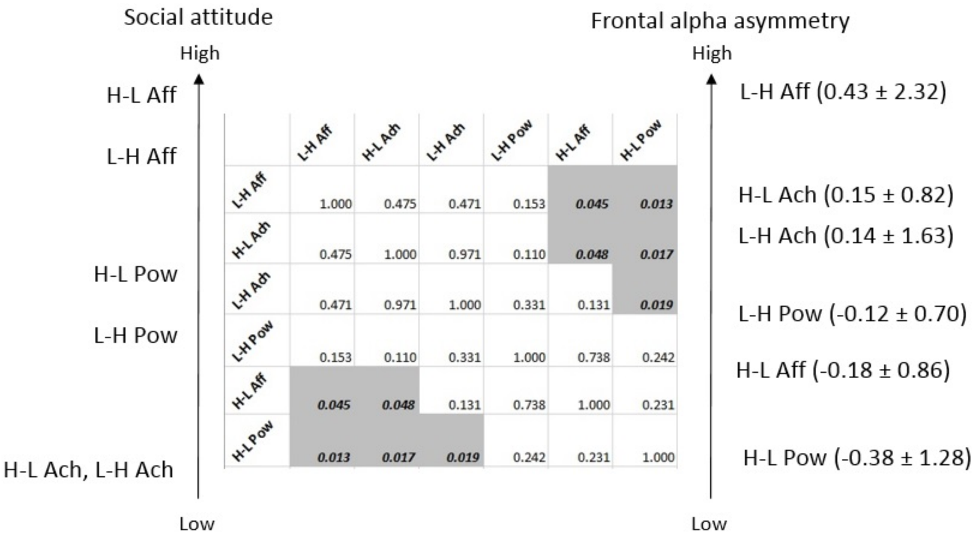
(a) IPP



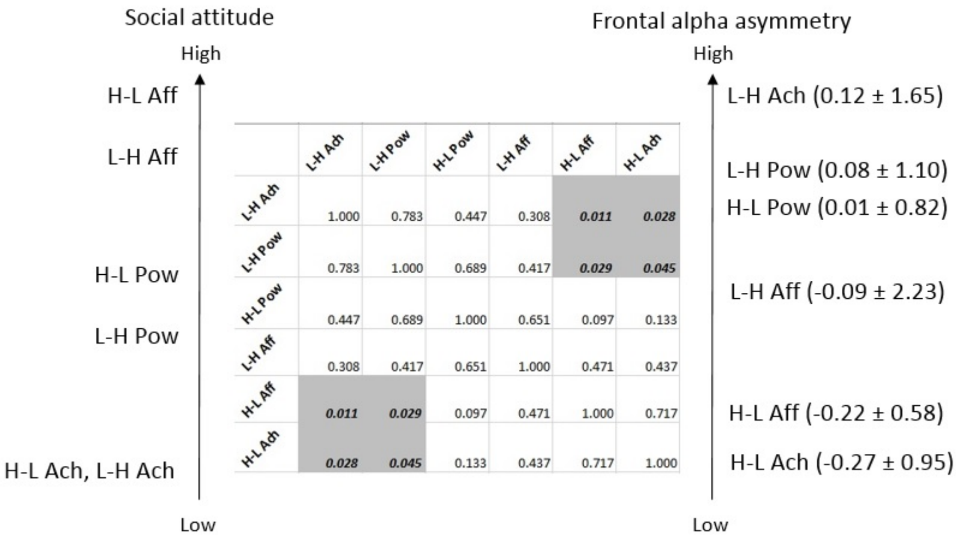
	L-H Aff	L-H Ach	L-H Pow	H-L Pow	H-L Aff	H-L Ach
L-H Aff	1.000	0.782	0.645	0.436	0.283	0.269
L-H Ach	0.782	1.000	0.802	0.553	0.317	0.228
L-H Pow	0.645	0.802	1.000	0.765	0.232	***0.025***
H-L Pow	0.436	0.553	0.765	1.000	0.557	0.246
H-L Aff	0.283	0.317	0.232	0.557	1.000	0.235
H-L Ach	0.269	0.228	***0.025***	0.246	0.235	1.000

(b) Action

Figure D.17: Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

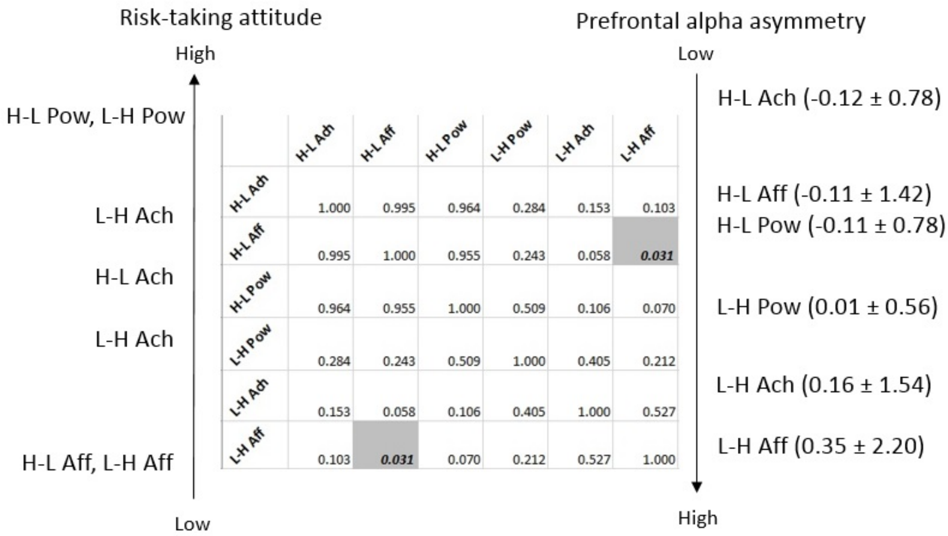


(a) Money feedback



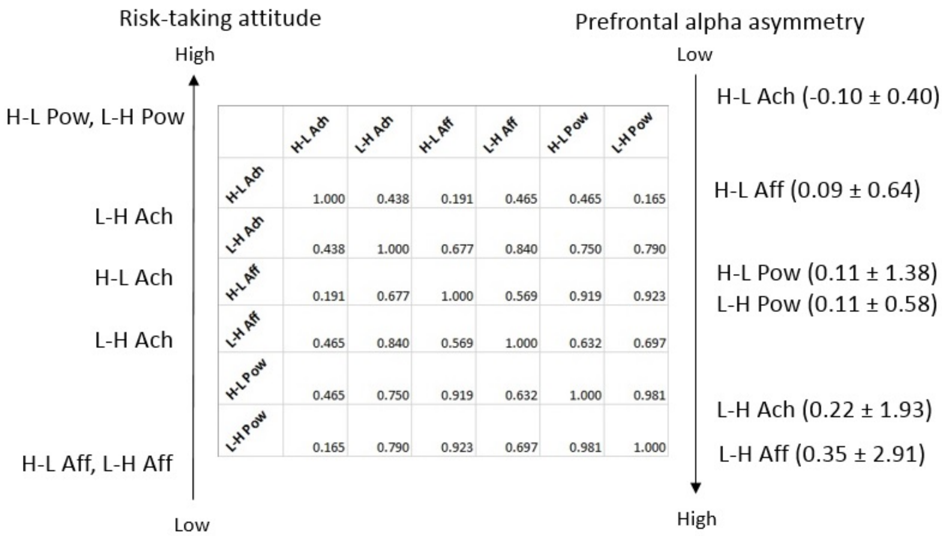
(b) Satisfaction feedback

Figure D.18: Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	H-L Aff	H-L Pow	L-H Pow	L-H Ach	L-H Aff
H-L Ach	1.000	0.995	0.964	0.284	0.153	0.103
H-L Aff	0.995	1.000	0.955	0.243	0.058	***0.031***
H-L Pow	0.964	0.955	1.000	0.509	0.106	0.070
L-H Pow	0.284	0.243	0.509	1.000	0.405	0.212
L-H Ach	0.153	0.058	0.106	0.405	1.000	0.527
L-H Aff	0.103	***0.031***	0.070	0.212	0.527	1.000

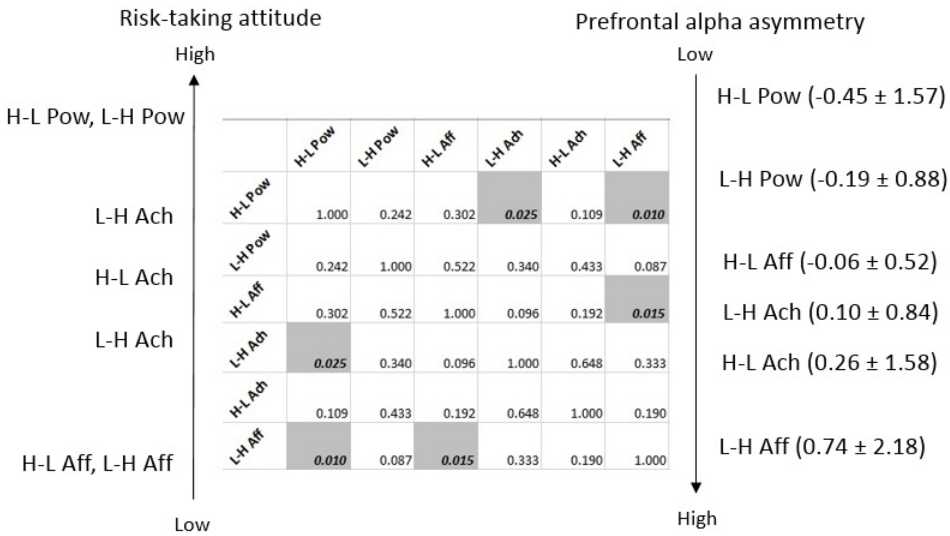
(a) IPP



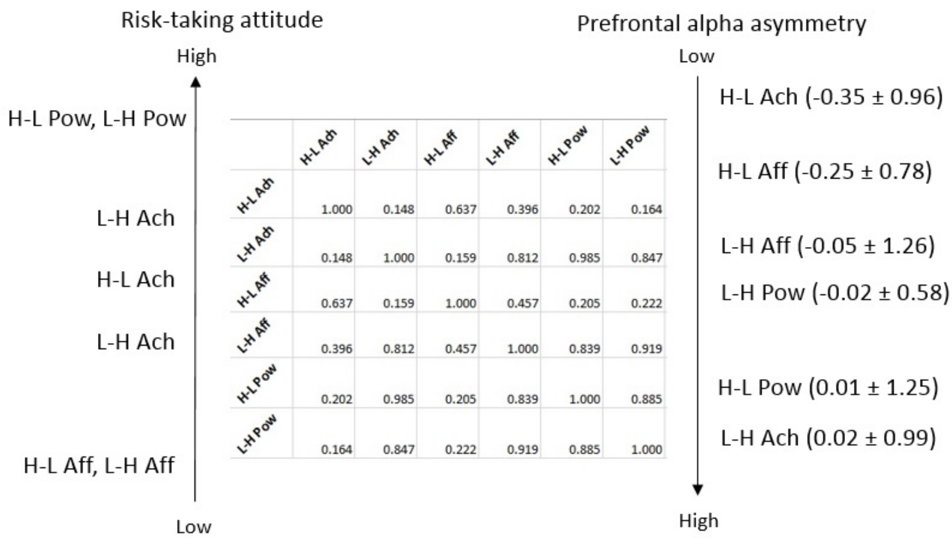
	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.438	0.191	0.465	0.465	0.165
L-H Ach	0.438	1.000	0.677	0.840	0.750	0.790
H-L Aff	0.191	0.677	1.000	0.569	0.919	0.923
L-H Aff	0.465	0.840	0.569	1.000	0.632	0.697
H-L Pow	0.465	0.750	0.919	0.632	1.000	0.981
L-H Pow	0.165	0.790	0.923	0.697	0.981	1.000

(b) Action

Figure D.19: Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

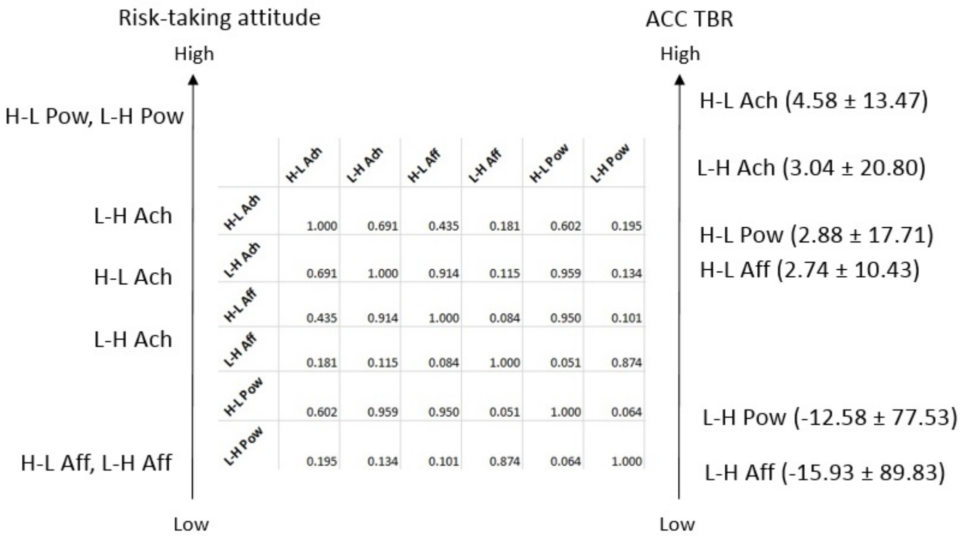


(a) Money feedback



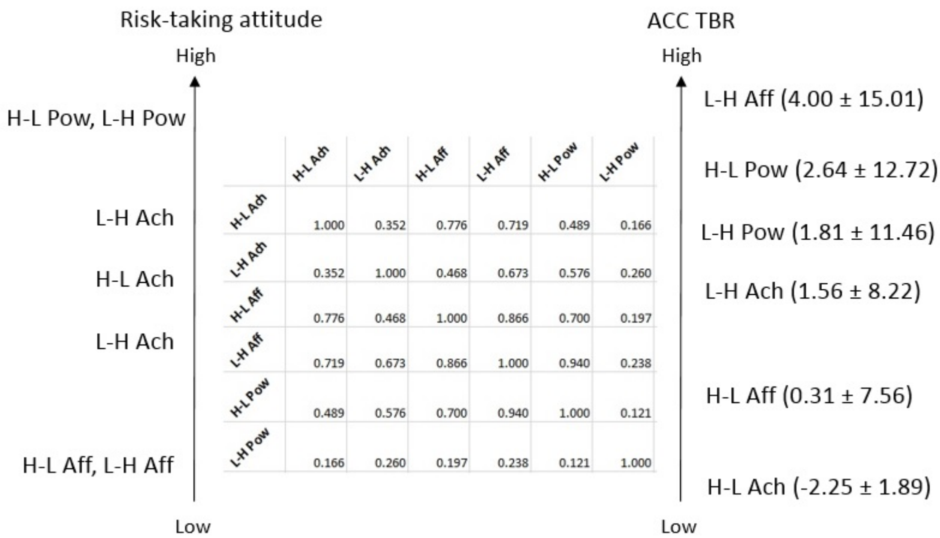
(b) Satisfaction feedback

Figure D.20: Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.691	0.435	0.181	0.602	0.195
L-H Ach	0.691	1.000	0.914	0.115	0.959	0.134
H-L Aff	0.435	0.914	1.000	0.084	0.950	0.101
L-H Aff	0.181	0.115	0.084	1.000	0.051	0.874
H-L Pow	0.602	0.959	0.950	0.051	1.000	0.064
L-H Pow	0.195	0.134	0.101	0.874	0.064	1.000

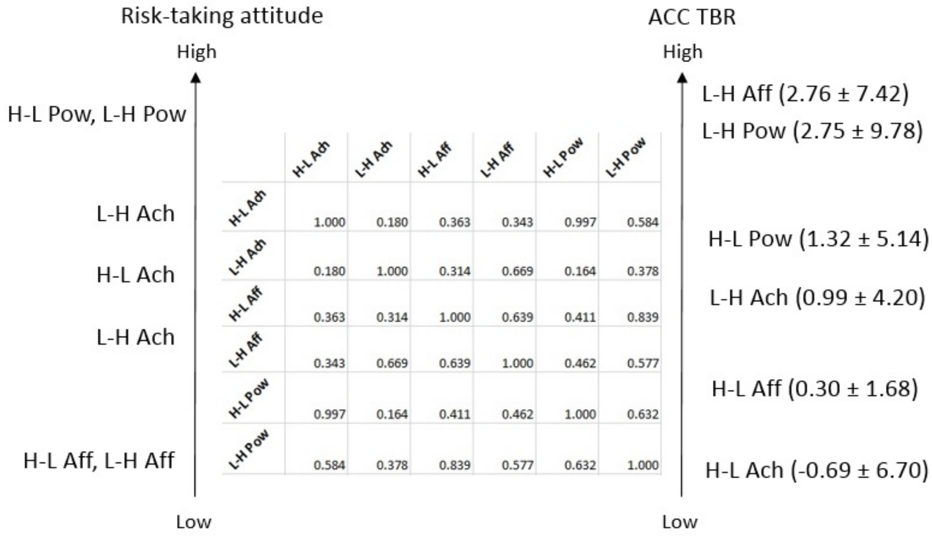
(a) IPP



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.352	0.776	0.719	0.489	0.166
L-H Ach	0.352	1.000	0.468	0.673	0.576	0.260
H-L Aff	0.776	0.468	1.000	0.866	0.700	0.197
L-H Aff	0.719	0.673	0.866	1.000	0.940	0.238
H-L Pow	0.489	0.576	0.700	0.940	1.000	0.121
L-H Pow	0.166	0.260	0.197	0.238	0.121	1.000

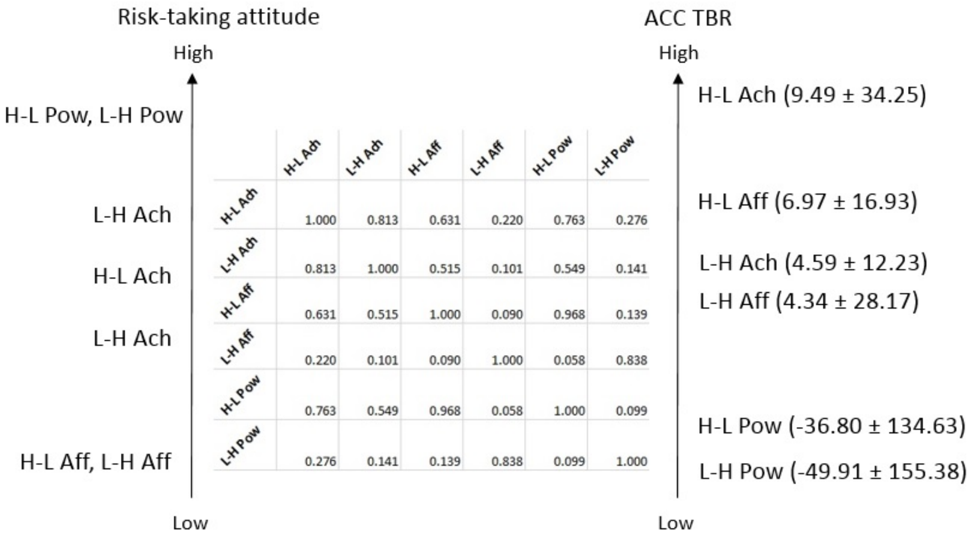
(b) Action

Figure D.21: Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.180	0.363	0.343	0.997	0.584
L-H Ach	0.180	1.000	0.314	0.669	0.164	0.378
H-L Aff	0.363	0.314	1.000	0.639	0.411	0.839
L-H Aff	0.343	0.669	0.639	1.000	0.462	0.577
H-L Pow	0.997	0.164	0.411	0.462	1.000	0.632
L-H Pow	0.584	0.378	0.839	0.577	0.632	1.000

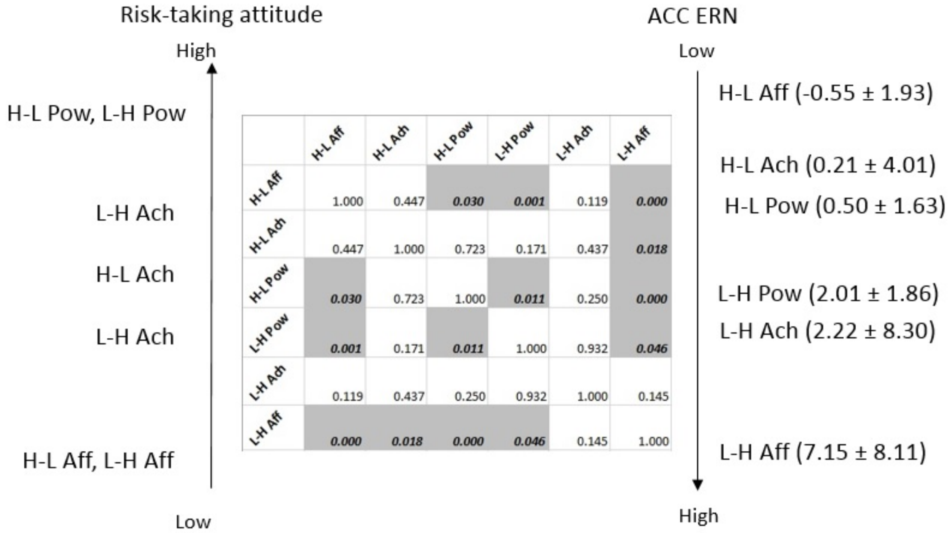
(a) Money feedback



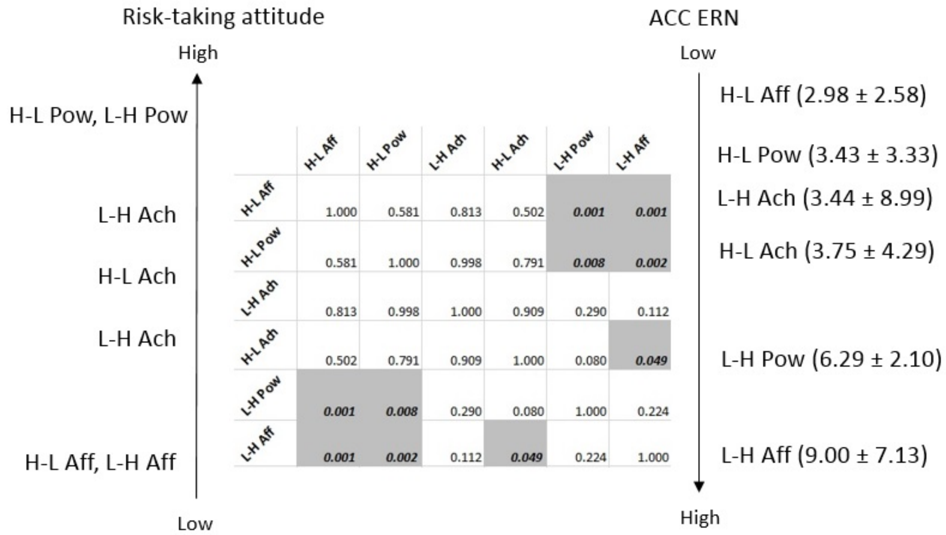
	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.813	0.631	0.220	0.763	0.276
L-H Ach	0.813	1.000	0.515	0.101	0.549	0.141
H-L Aff	0.631	0.515	1.000	0.090	0.968	0.139
L-H Aff	0.220	0.101	0.090	1.000	0.058	0.838
H-L Pow	0.763	0.549	0.968	0.058	1.000	0.099
L-H Pow	0.276	0.141	0.139	0.838	0.099	1.000

(b) Satisfaction feedback

Figure D.22: Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

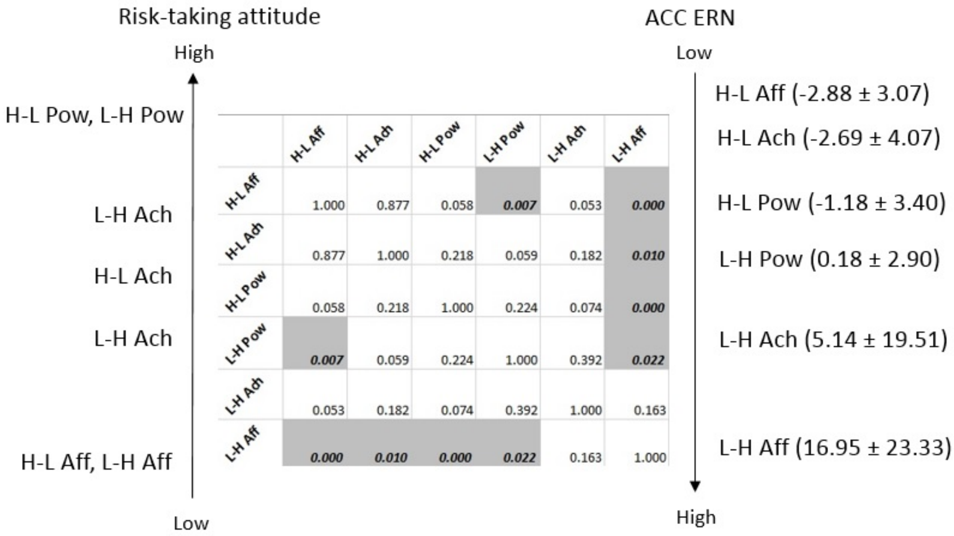


(a) IPP

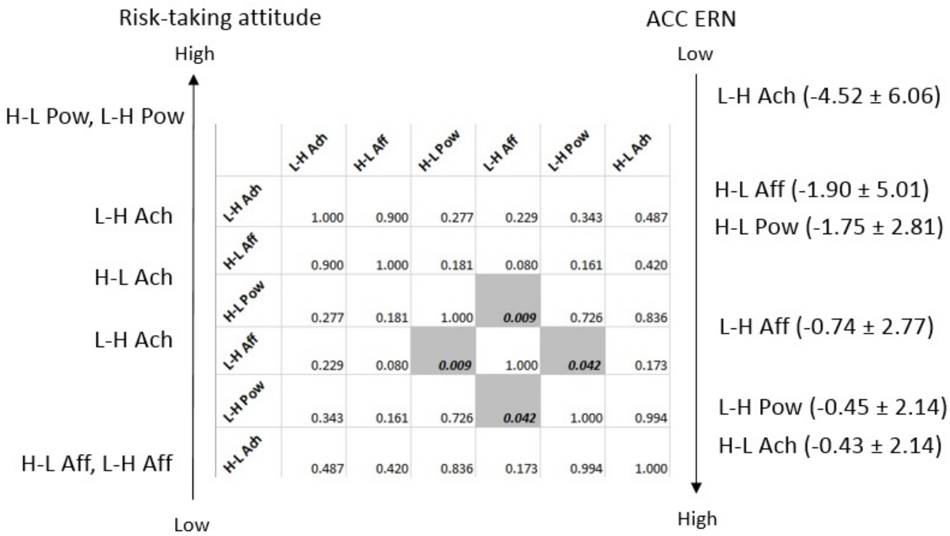


(b) Action

Figure D.23: Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

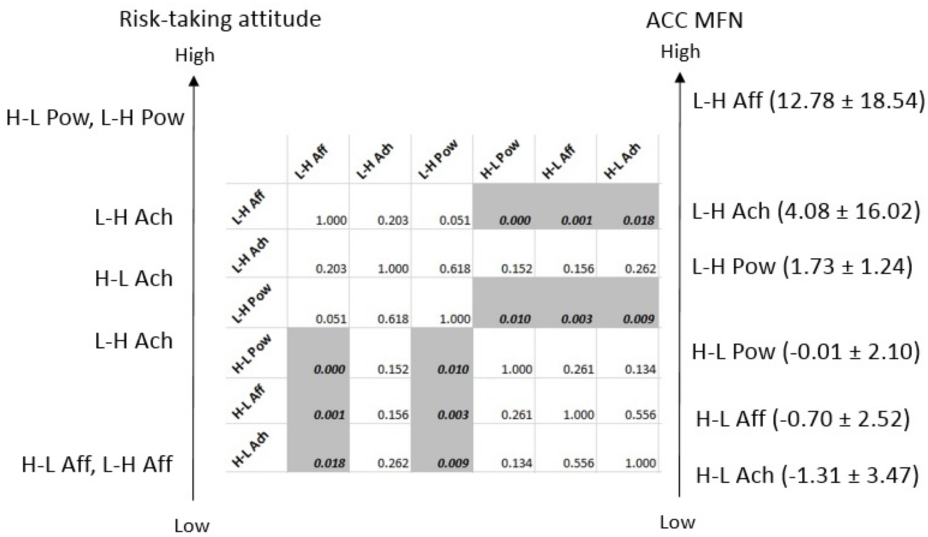


(a) Money feedback

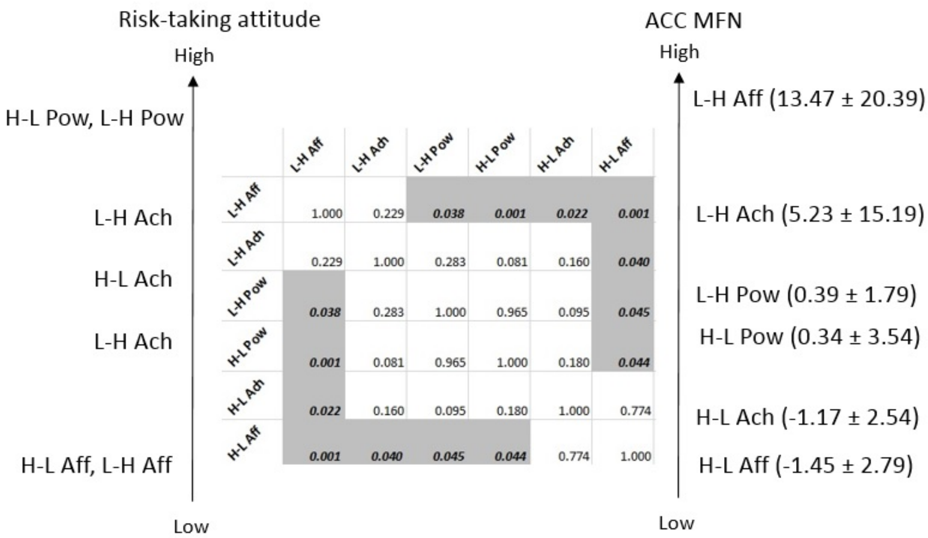


(b) Satisfaction feedback

Figure D.24: Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

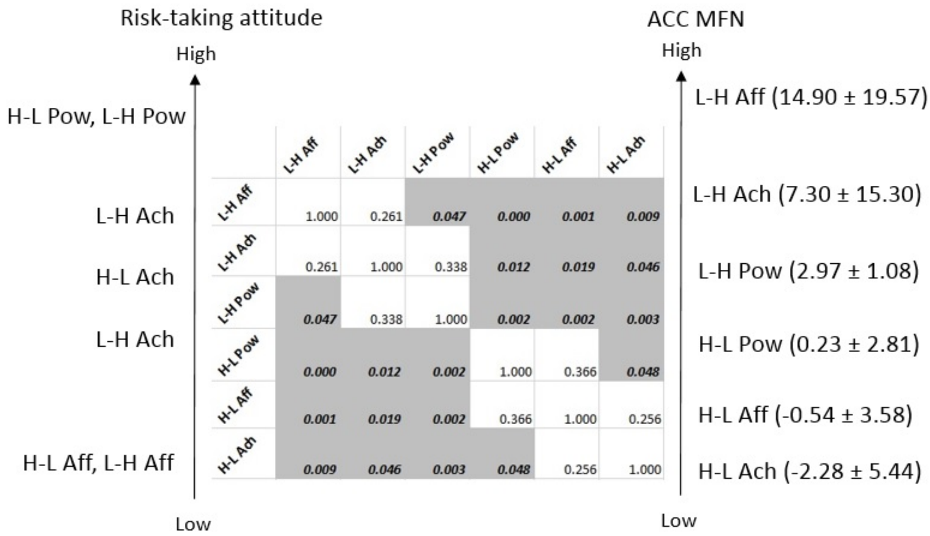


(a) IPP

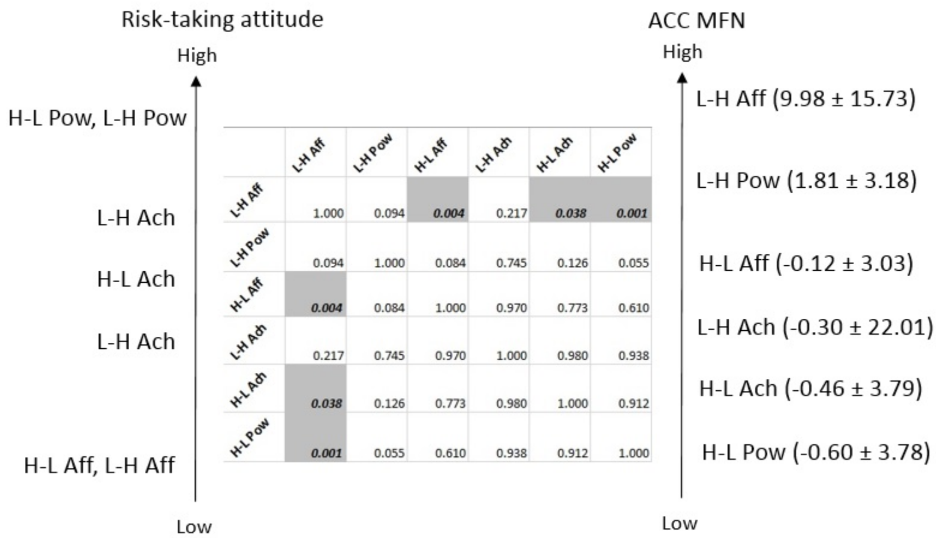


(b) Action

Figure D.25: Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

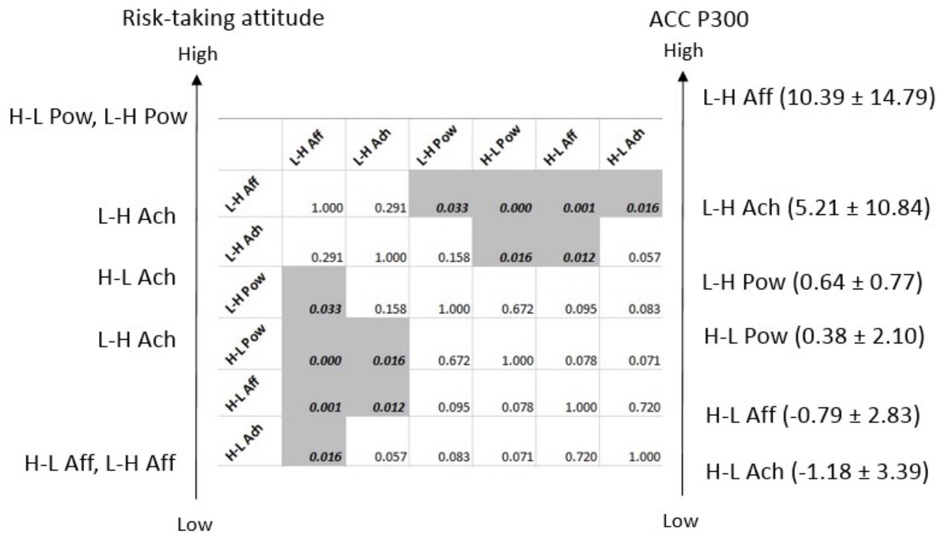


(a) Money feedback

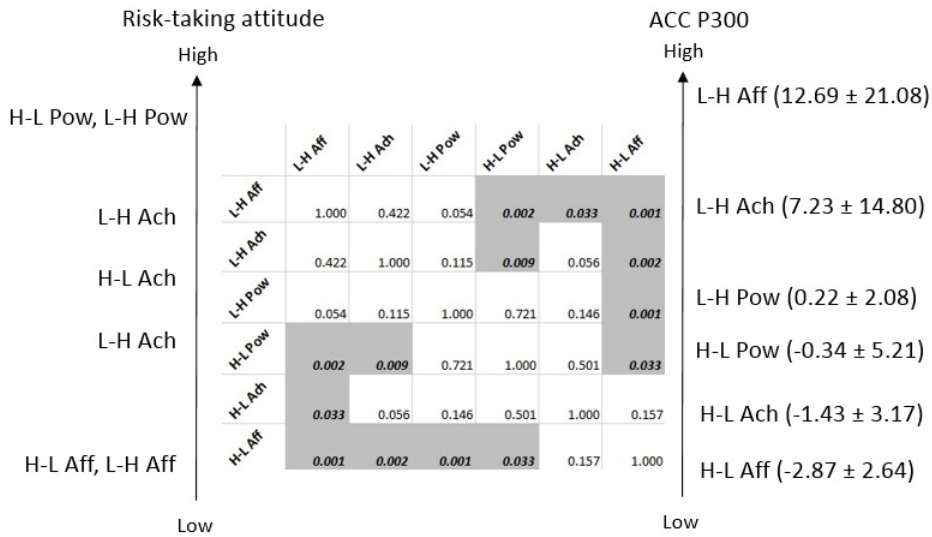


(b) Satisfaction feedback

Figure D.26: Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

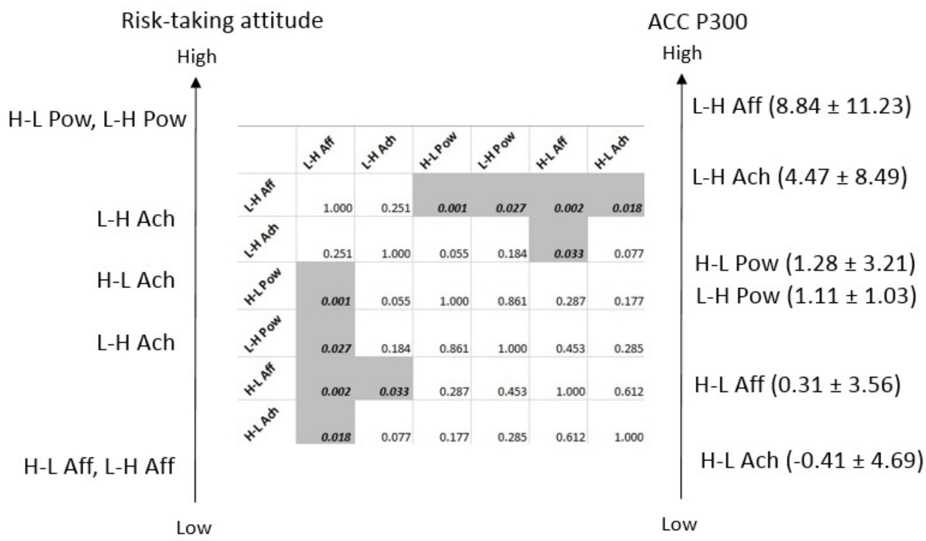


(a) IPP

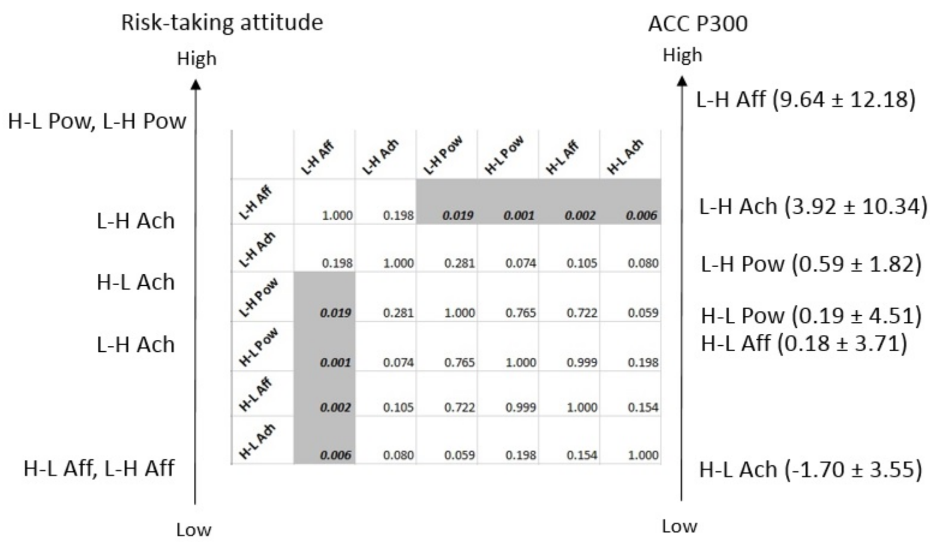


(b) Action

Figure D.27: Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

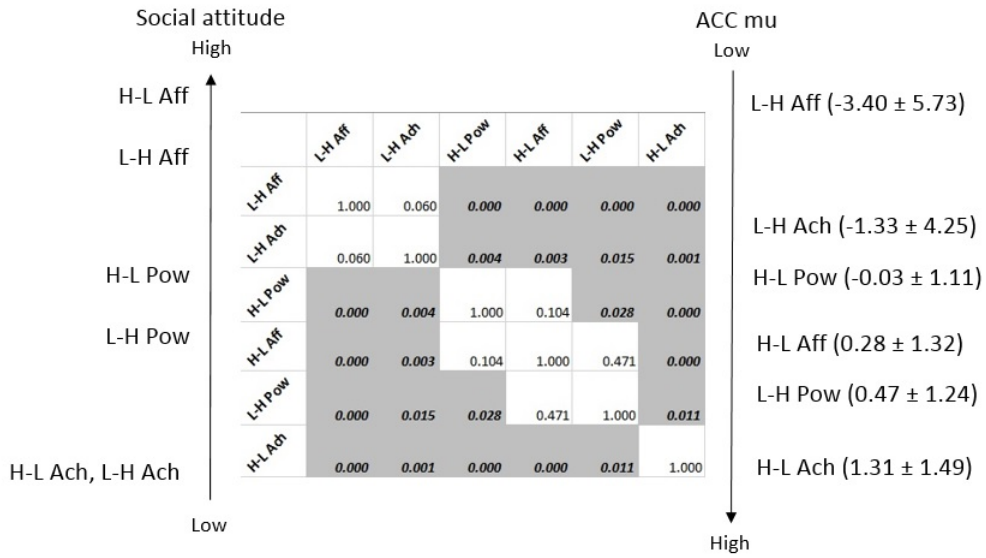


(a) Money feedback

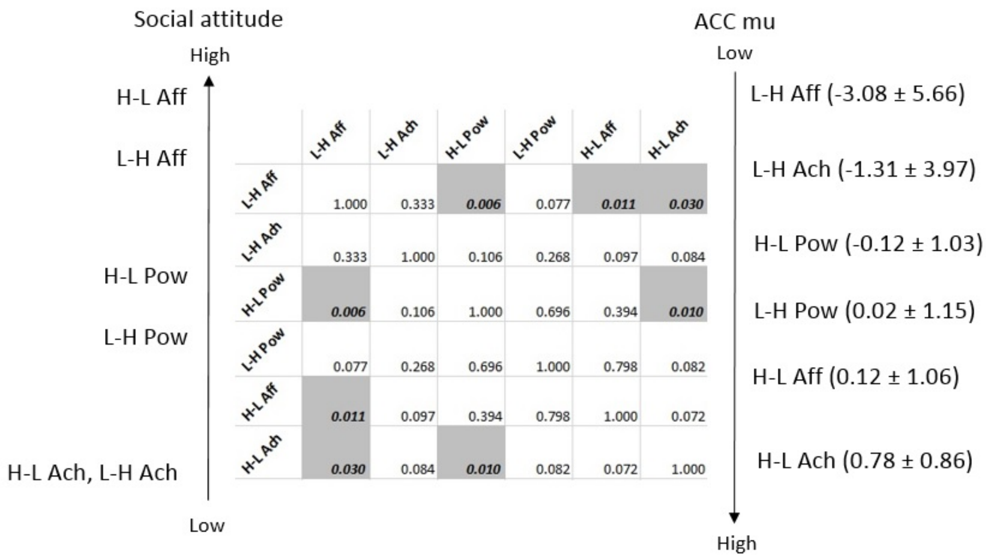


(b) Satisfaction feedback

Figure D.28: Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Defector Dan. The p-value of independent t-test between hope and fear components of each motivation is presented.

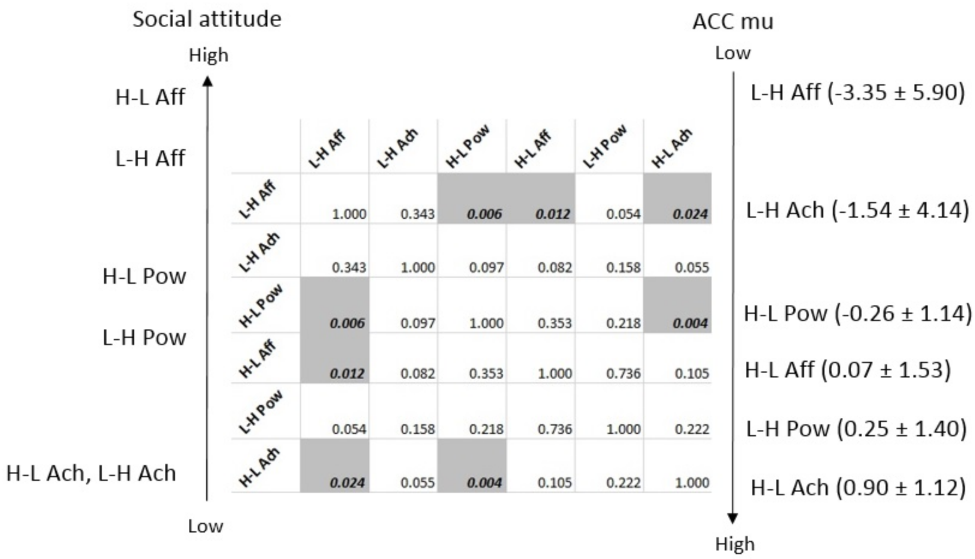


(a) IPP

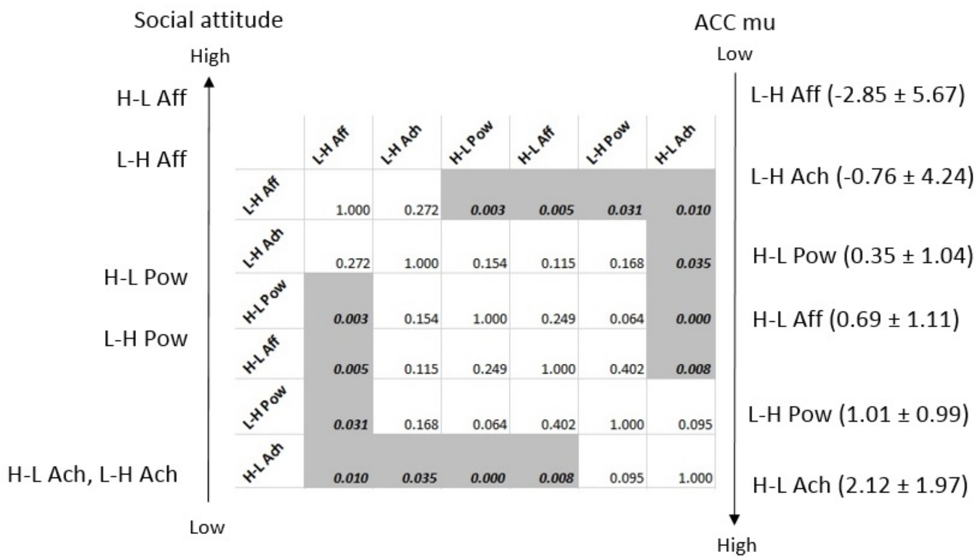


(b) Action

Figure D.29: Results of using ACC mu band in IPP and action to reveal social attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

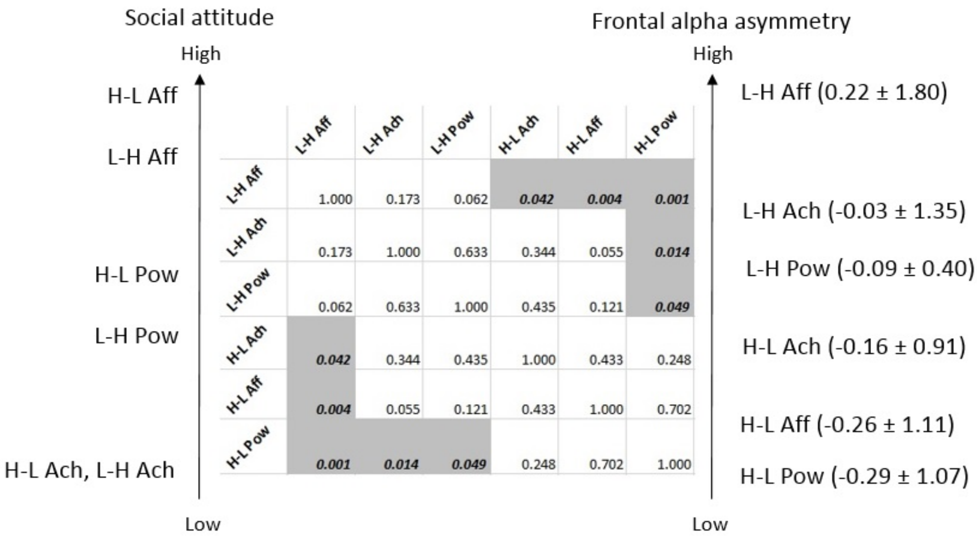


(a) Money feedback

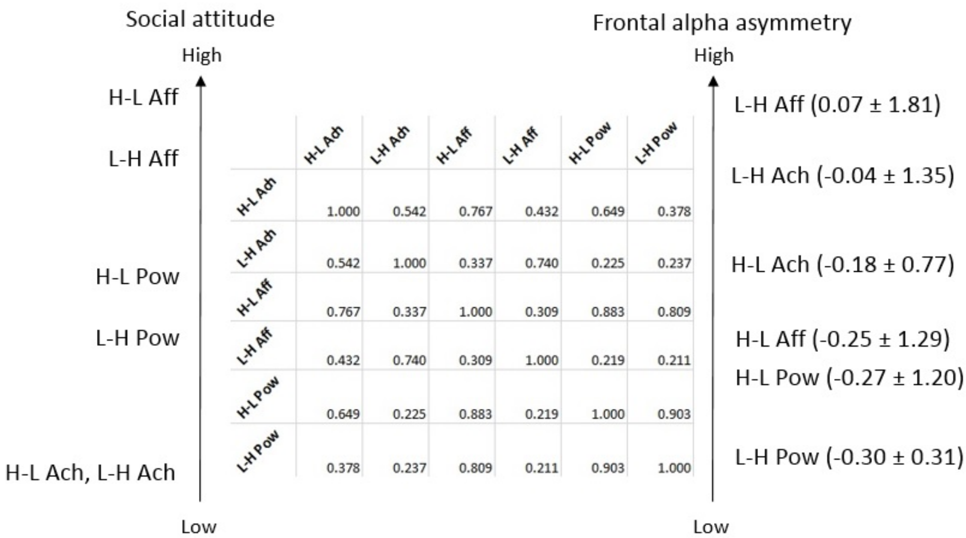


(b) Satisfaction feedback

Figure D.30: Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

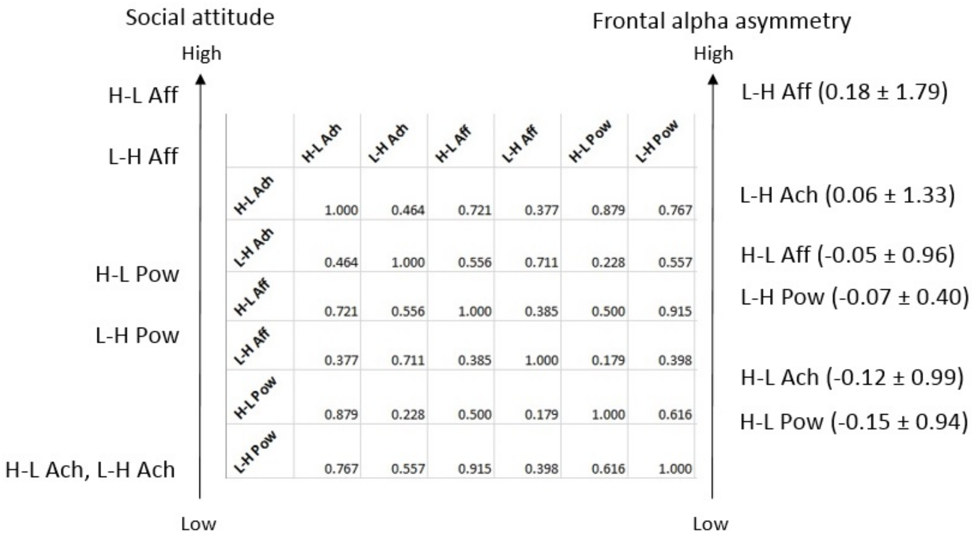


(a) IPP

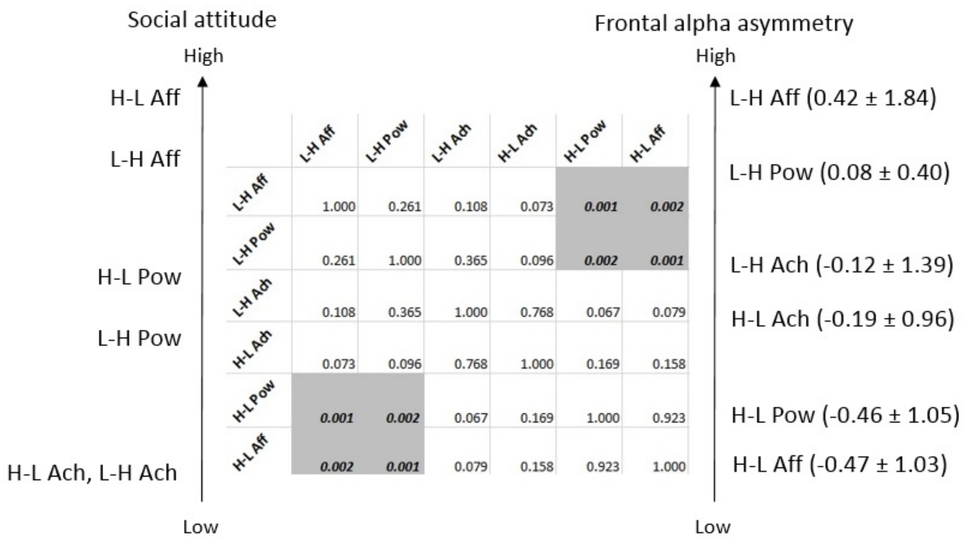


(b) Action

Figure D.31: Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

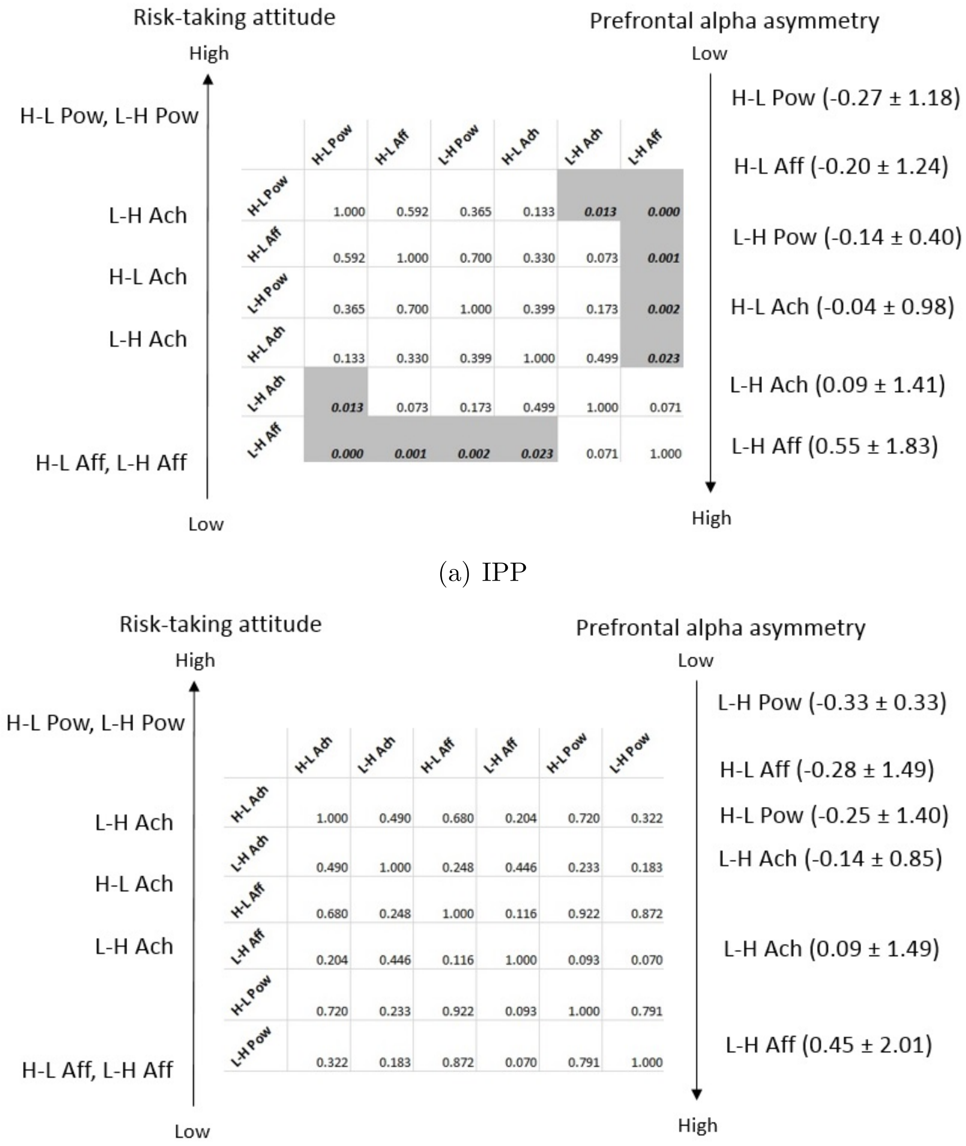


(a) Money feedback



(b) Satisfaction feedback

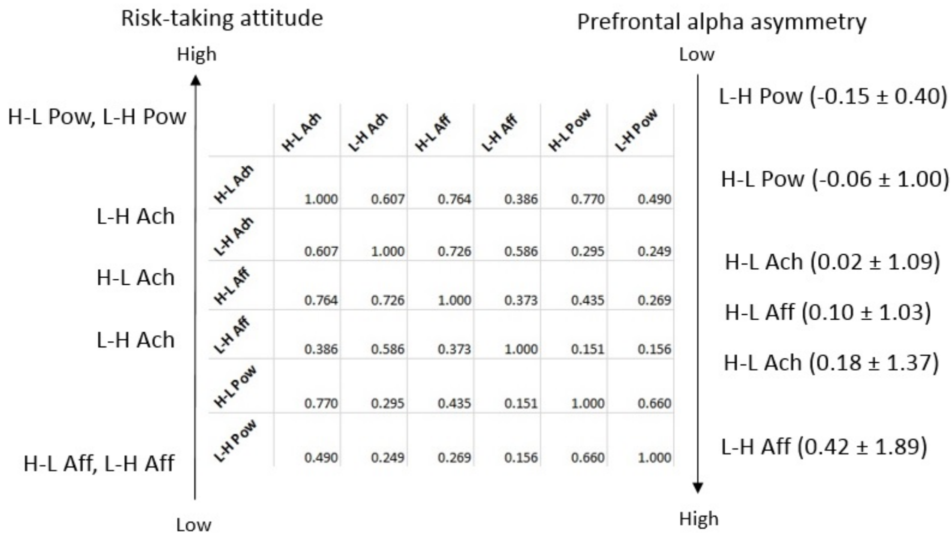
Figure D.32: Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



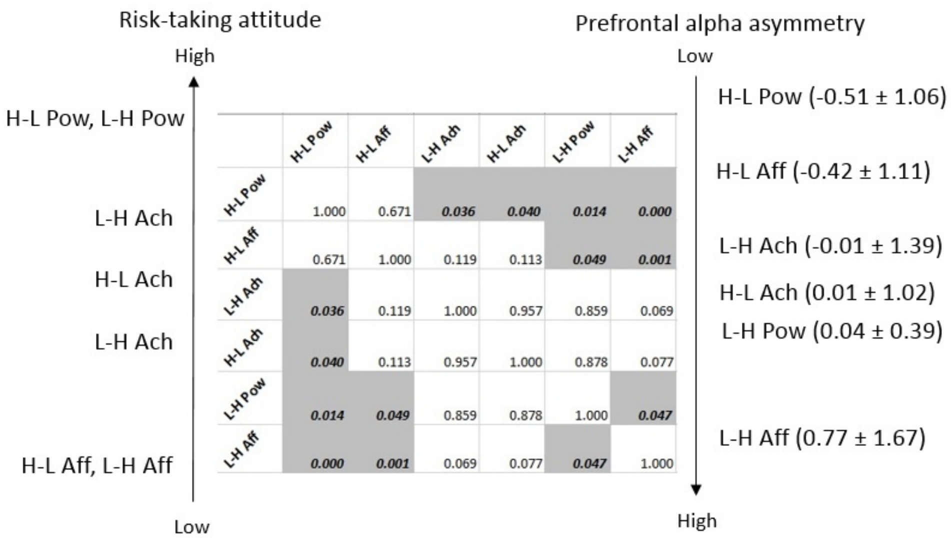
(a) IPP

(b) Action

Figure D.33: Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

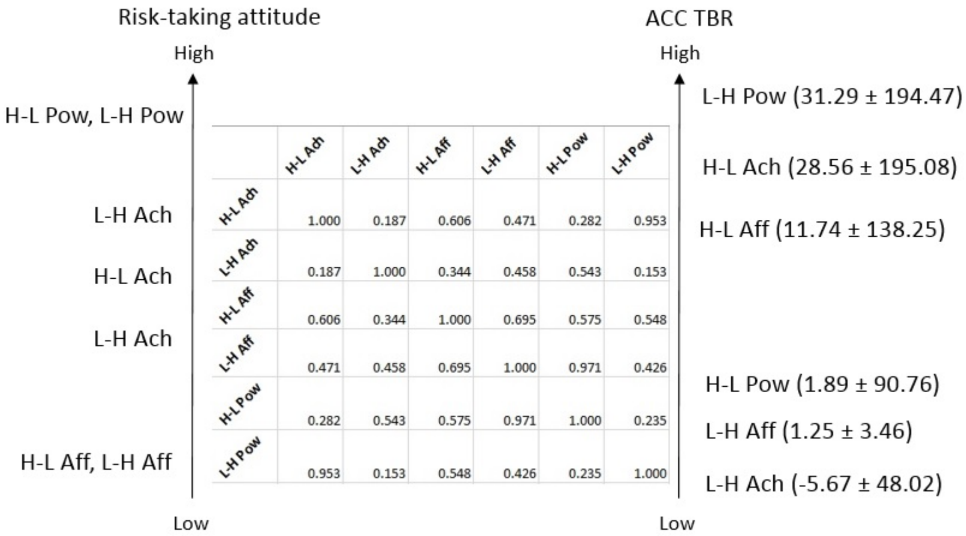


(a) Money feedback



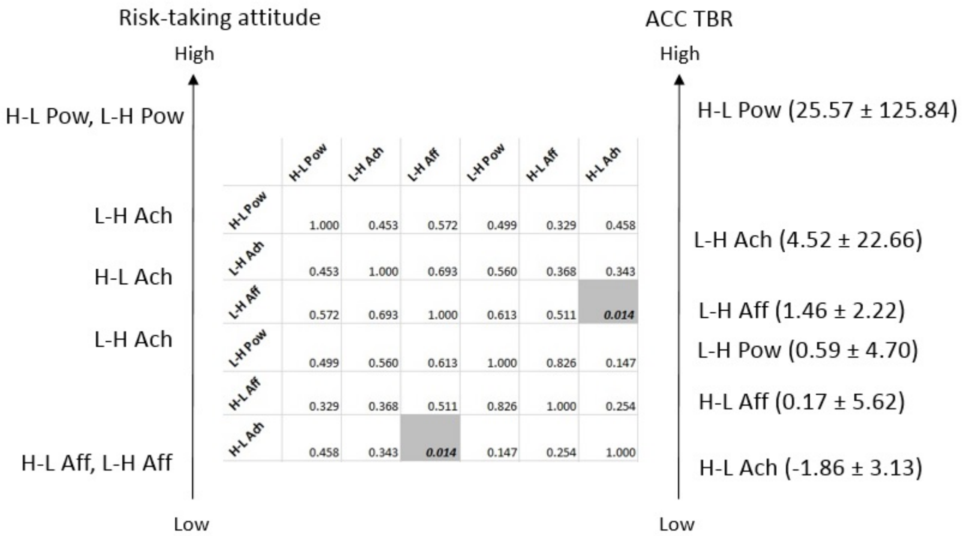
(b) Satisfaction feedback

Figure D.34: Results of using Prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.187	0.606	0.471	0.282	0.953
L-H Ach	0.187	1.000	0.344	0.458	0.543	0.153
H-L Aff	0.606	0.344	1.000	0.695	0.575	0.548
L-H Aff	0.471	0.458	0.695	1.000	0.971	0.426
H-L Pow	0.282	0.543	0.575	0.971	1.000	0.235
L-H Pow	0.953	0.153	0.548	0.426	0.235	1.000

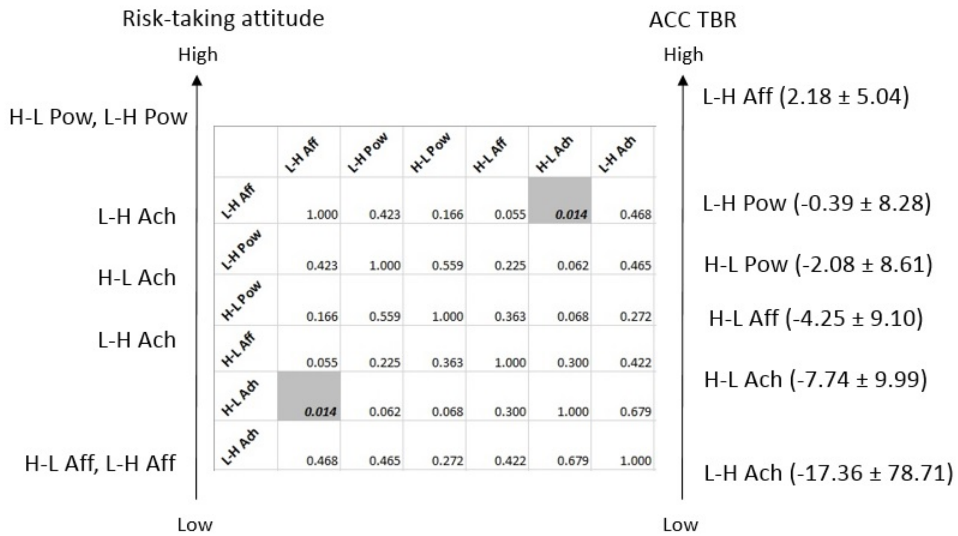
(a) IPP



	H-L Pow	L-H Ach	L-H Aff	L-H Pow	H-L Aff	H-L Ach
H-L Pow	1.000	0.453	0.572	0.499	0.329	0.458
L-H Ach	0.453	1.000	0.693	0.560	0.368	0.343
L-H Aff	0.572	0.693	1.000	0.613	0.511	***0.014***
L-H Pow	0.499	0.560	0.613	1.000	0.826	0.147
H-L Aff	0.329	0.368	0.511	0.826	1.000	0.254
H-L Ach	0.458	0.343	***0.014***	0.147	0.254	1.000

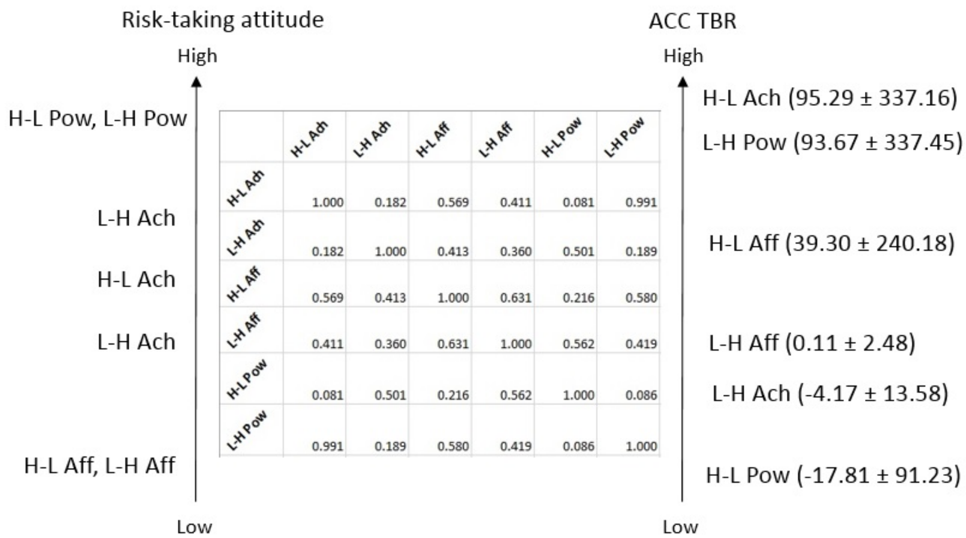
(b) Action

Figure D.35: Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Pow	H-L Pow	H-L Aff	H-L Ach	L-H Ach
L-H Aff	1.000	0.423	0.166	0.055	*0.014*	0.468
L-H Pow	0.423	1.000	0.559	0.225	0.062	0.465
H-L Pow	0.166	0.559	1.000	0.363	0.068	0.272
H-L Aff	0.055	0.225	0.363	1.000	0.300	0.422
H-L Ach	*0.014*	0.062	0.068	0.300	1.000	0.679
L-H Ach	0.468	0.465	0.272	0.422	0.679	1.000

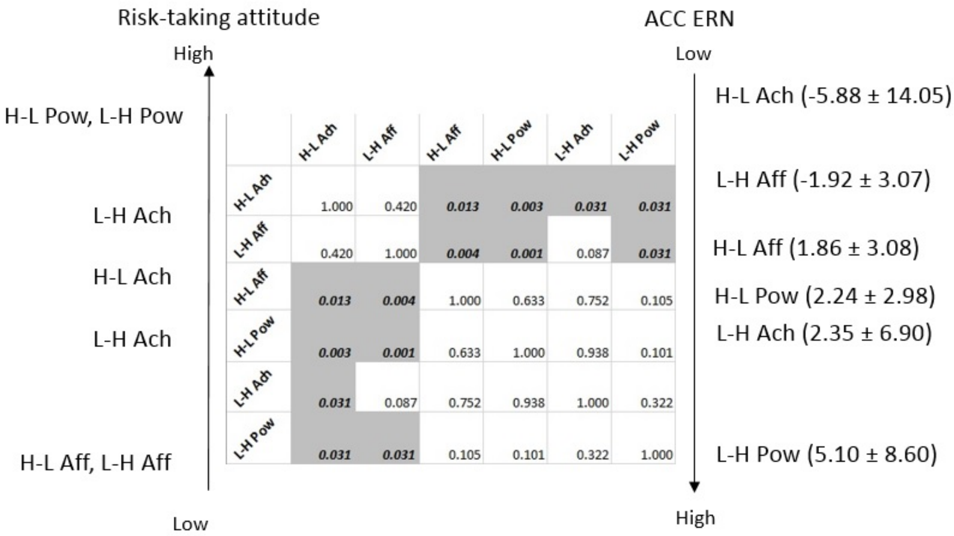
(a) Money feedback



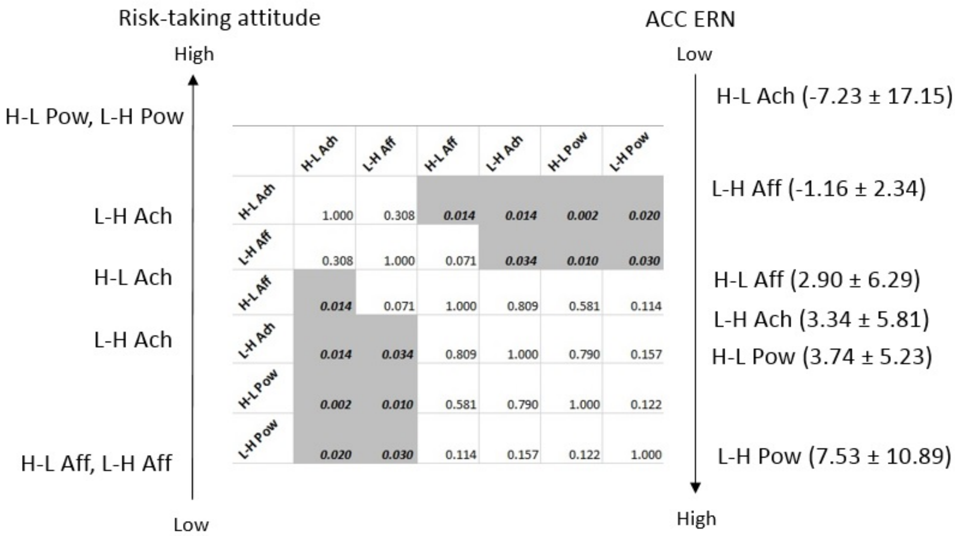
	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.182	0.569	0.411	0.081	0.991
L-H Ach	0.182	1.000	0.413	0.360	0.501	0.189
H-L Aff	0.569	0.413	1.000	0.631	0.216	0.580
L-H Aff	0.411	0.360	0.631	1.000	0.562	0.419
H-L Pow	0.081	0.501	0.216	0.562	1.000	0.086
L-H Pow	0.991	0.189	0.580	0.419	0.086	1.000

(b) Satisfaction feedback

Figure D.36: Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

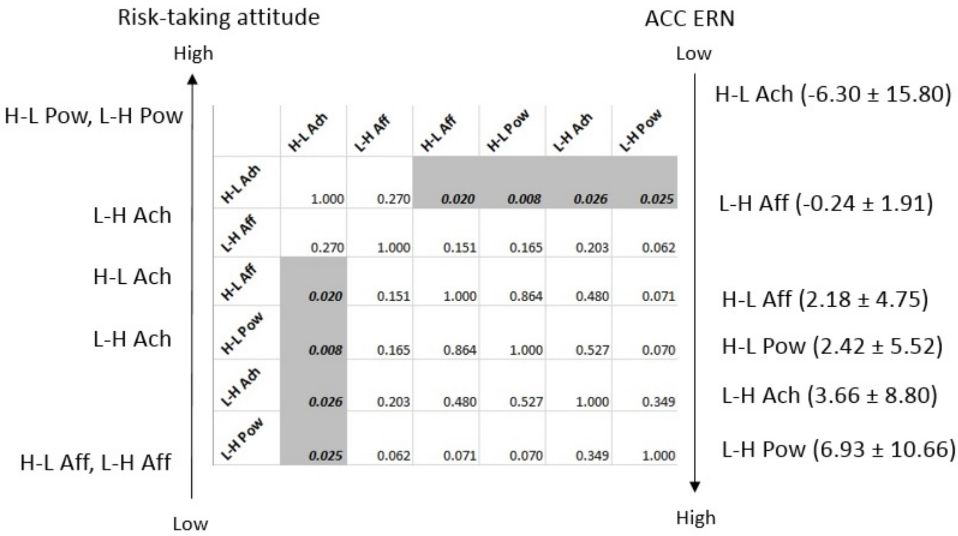


(a) IPP



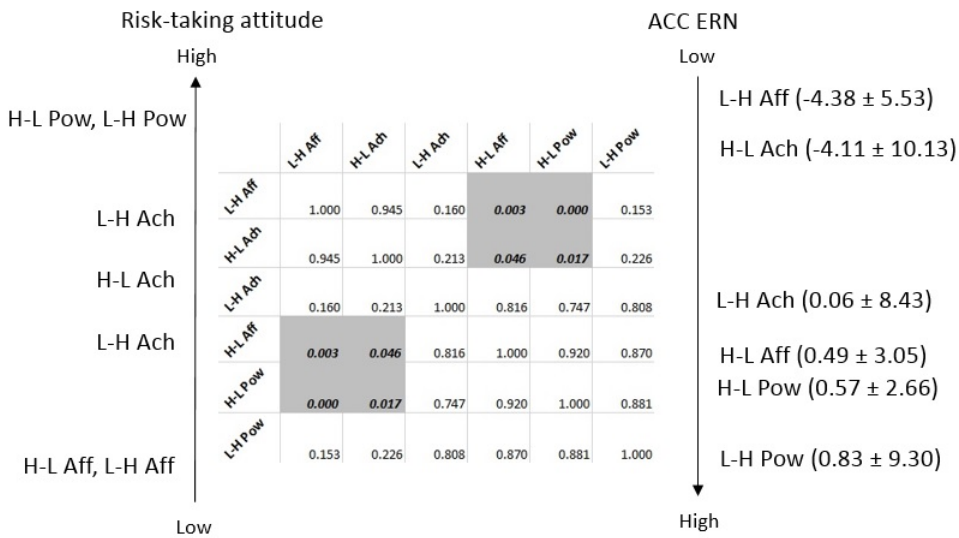
(b) Action

Figure D.37: Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Aff	H-L Aff	H-L Pow	L-H Ach	L-H Pow
H-L Ach	1.000	0.270	***0.020***	***0.008***	***0.026***	***0.025***
L-H Aff	0.270	1.000	0.151	0.165	0.203	0.062
H-L Aff	***0.020***	0.151	1.000	0.864	0.480	0.071
H-L Pow	***0.008***	0.165	0.864	1.000	0.527	0.070
L-H Ach	***0.026***	0.203	0.480	0.527	1.000	0.349
L-H Pow	***0.025***	0.062	0.071	0.070	0.349	1.000

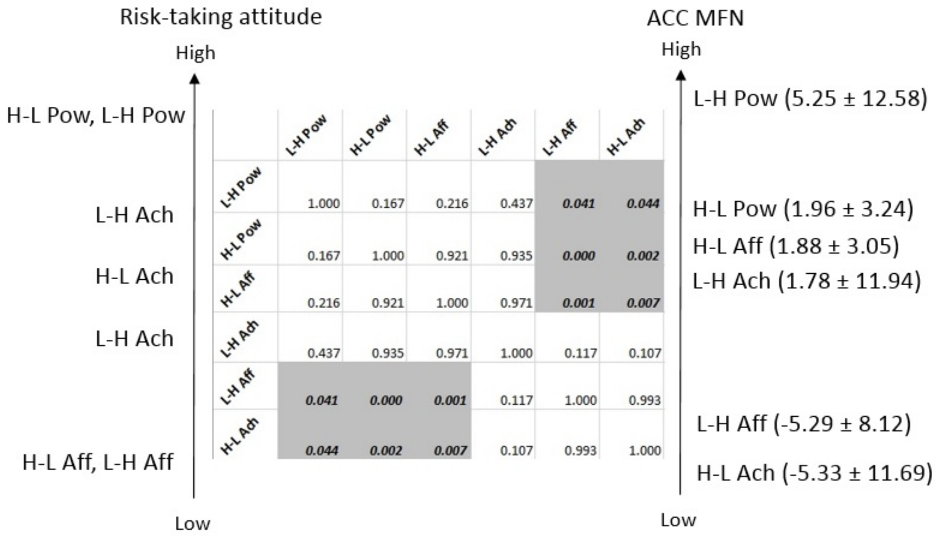
(a) Money feedback



	L-H Aff	H-L Ach	L-H Ach	H-L Aff	H-L Pow	L-H Pow
L-H Aff	1.000	0.945	0.160	***0.003***	***0.000***	0.153
H-L Ach	0.945	1.000	0.213	***0.046***	***0.017***	0.226
L-H Ach	0.160	0.213	1.000	0.816	0.747	0.808
H-L Aff	***0.003***	***0.046***	0.816	1.000	0.920	0.870
H-L Pow	***0.000***	***0.017***	0.747	0.920	1.000	0.881
L-H Pow	0.153	0.226	0.808	0.870	0.881	1.000

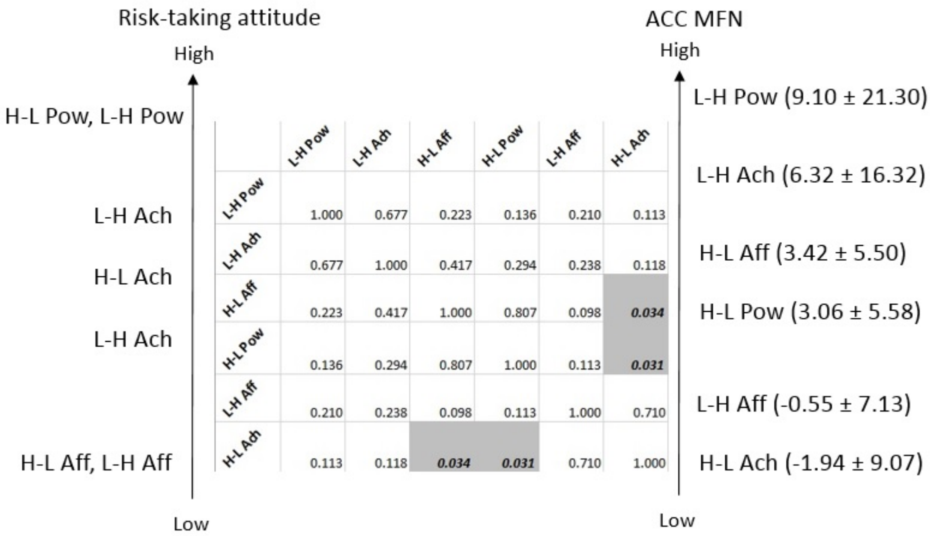
(b) Satisfaction feedback

Figure D.38: Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Pow	H-L Pow	H-L Aff	L-H Ach	L-H Aff	H-L Ach
L-H Pow	1.000	0.167	0.216	0.437	*0.041*	*0.044*
H-L Pow	0.167	1.000	0.921	0.935	*0.000*	*0.002*
H-L Aff	0.216	0.921	1.000	0.971	*0.001*	*0.007*
L-H Ach	0.437	0.935	0.971	1.000	0.117	0.107
L-H Aff	*0.041*	*0.000*	*0.001*	0.117	1.000	0.993
H-L Ach	*0.044*	*0.002*	*0.007*	0.107	0.993	1.000

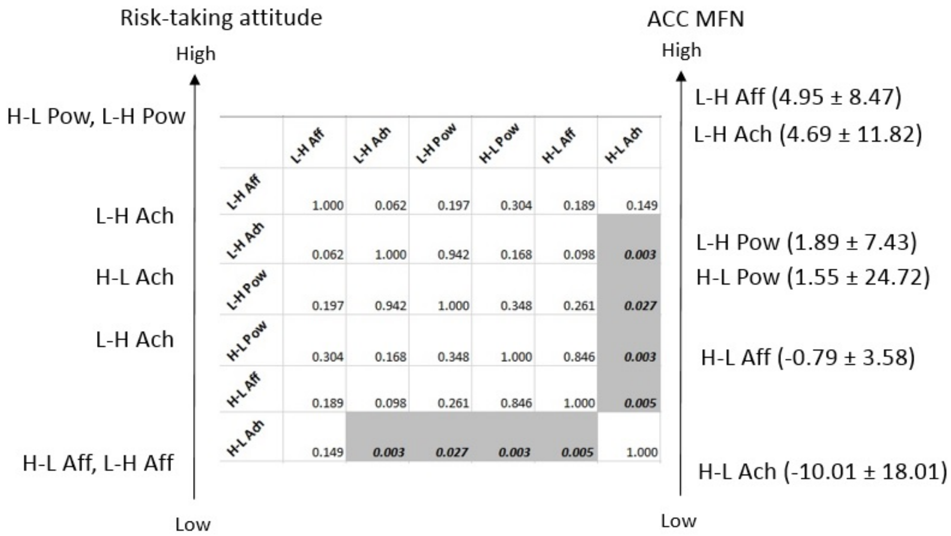
(a) IPP



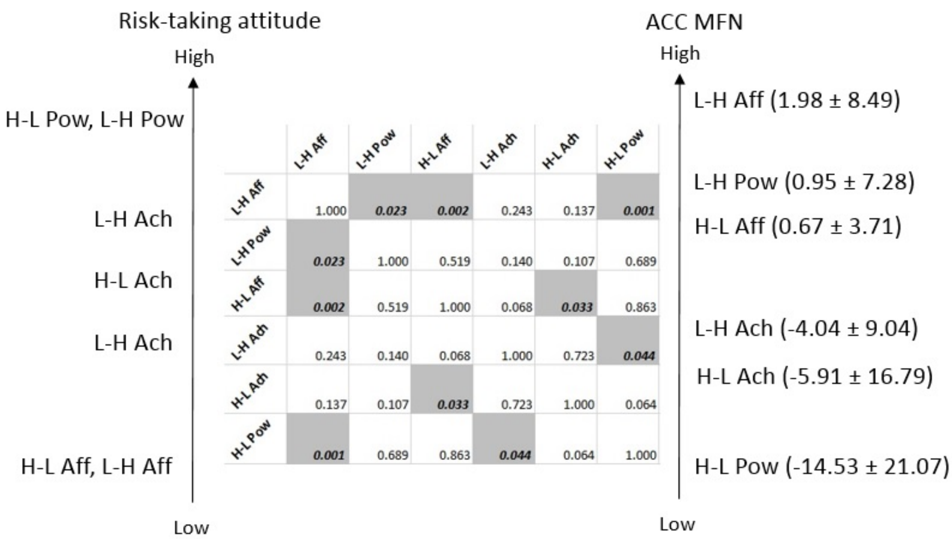
	L-H Pow	L-H Ach	H-L Aff	H-L Pow	L-H Aff	H-L Ach
L-H Pow	1.000	0.677	0.223	0.136	0.210	0.113
L-H Ach	0.677	1.000	0.417	0.294	0.238	0.118
H-L Aff	0.223	0.417	1.000	0.807	0.098	*0.034*
H-L Pow	0.136	0.294	0.807	1.000	0.113	*0.031*
L-H Aff	0.210	0.238	0.098	0.113	1.000	0.710
H-L Ach	0.113	0.118	*0.034*	*0.031*	0.710	1.000

(b) Action

Figure D.39: Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.

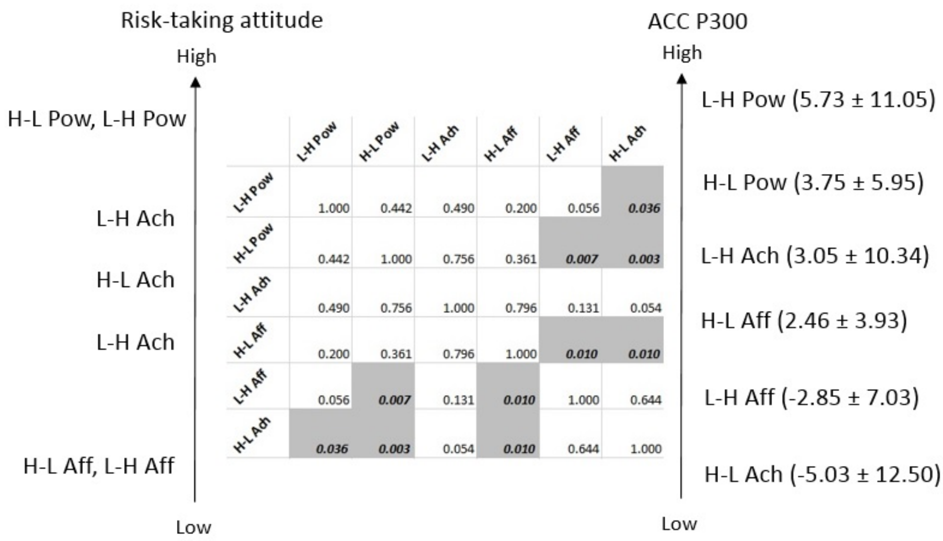


(a) Money feedback



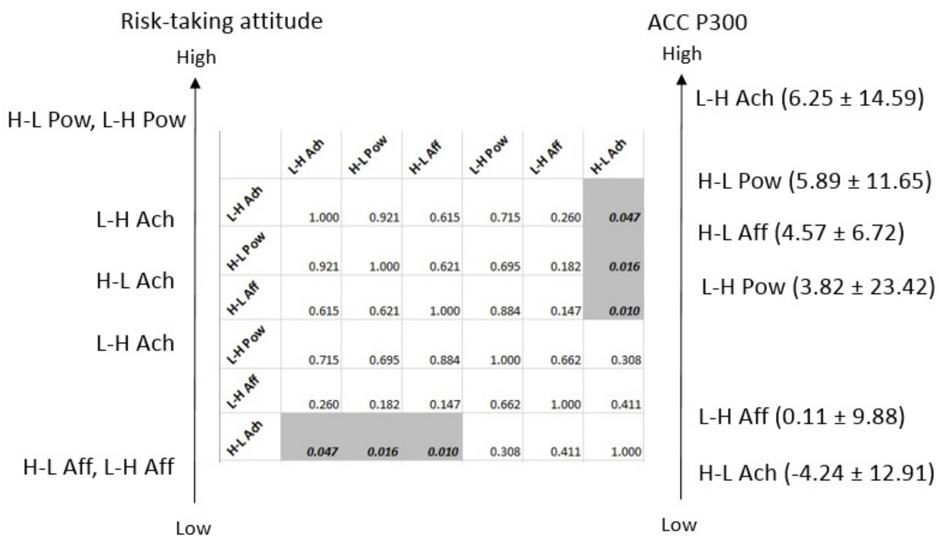
(b) Satisfaction feedback

Figure D.40: Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Pow	H-L Pow	L-H Ach	H-L Aff	L-H Aff	H-L Ach
L-H Pow	1.000	0.442	0.490	0.200	0.056	***0.036***
H-L Pow	0.442	1.000	0.756	0.361	***0.007***	***0.003***
L-H Ach	0.490	0.756	1.000	0.796	0.131	0.054
H-L Aff	0.200	0.361	0.796	1.000	***0.010***	***0.010***
L-H Aff	0.056	***0.007***	0.131	***0.010***	1.000	0.644
H-L Ach	***0.036***	***0.003***	0.054	***0.010***	0.644	1.000

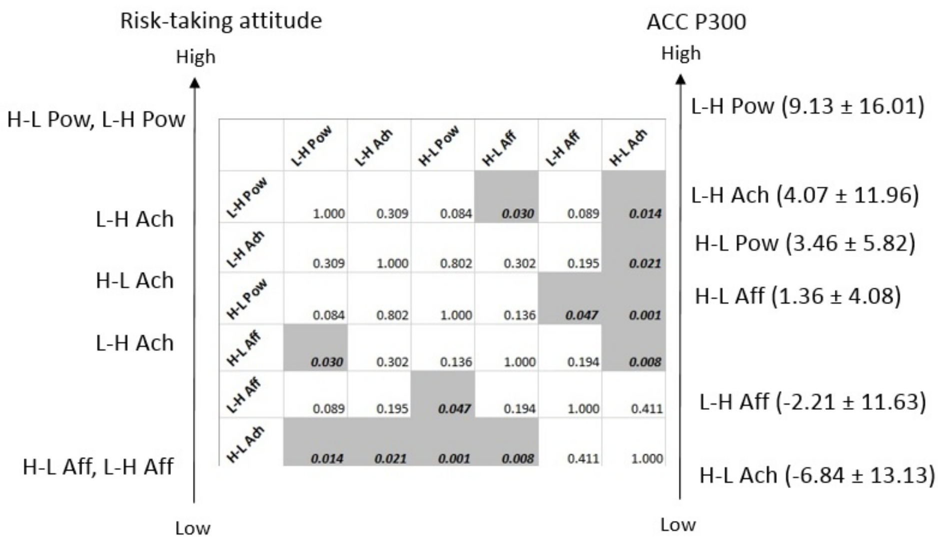
(a) IPP



	L-H Ach	H-L Pow	H-L Aff	L-H Pow	L-H Aff	H-L Ach
L-H Ach	1.000	0.921	0.615	0.715	0.260	***0.047***
H-L Pow	0.921	1.000	0.621	0.695	0.182	***0.016***
H-L Aff	0.615	0.621	1.000	0.884	0.147	***0.010***
L-H Pow	0.715	0.695	0.884	1.000	0.662	0.308
L-H Aff	0.260	0.182	0.147	0.662	1.000	0.411
H-L Ach	***0.047***	***0.016***	***0.010***	0.308	0.411	1.000

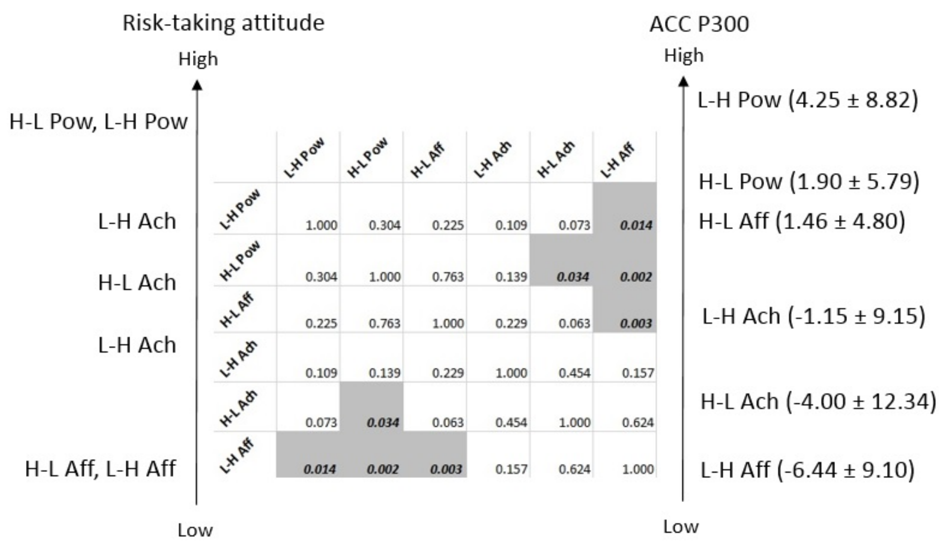
(b) Action

Figure D.41: Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Pow	L-H Ach	H-L Pow	H-L Aff	L-H Aff	H-L Ach
L-H Pow	1.000	0.309	0.084	*0.030*	0.089	*0.014*
L-H Ach	0.309	1.000	0.802	0.302	0.195	*0.021*
H-L Pow	0.084	0.802	1.000	0.136	*0.047*	*0.001*
H-L Aff	*0.030*	0.302	0.136	1.000	0.194	*0.008*
L-H Aff	0.089	0.195	*0.047*	0.194	1.000	0.411
H-L Ach	*0.014*	*0.021*	*0.001*	*0.008*	0.411	1.000

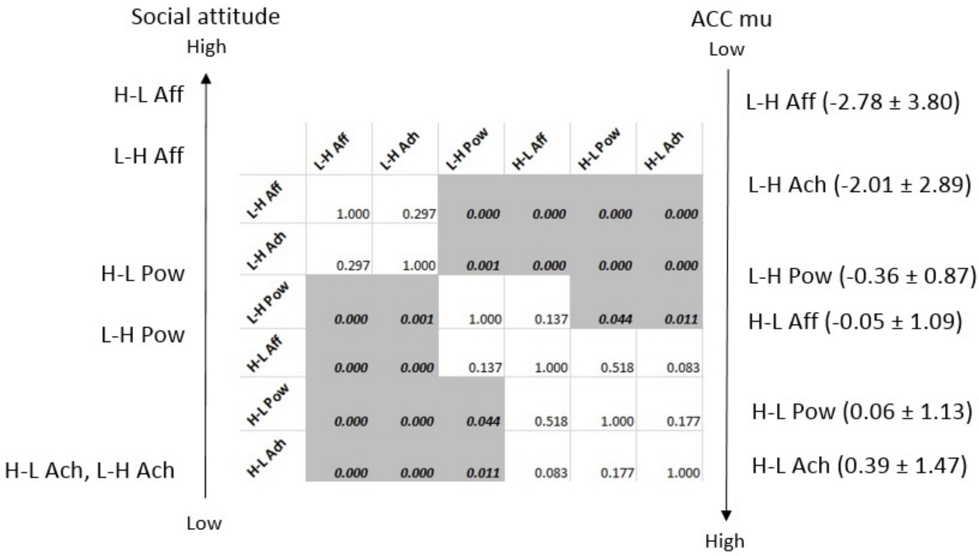
(a) Money feedback



	L-H Pow	H-L Pow	H-L Aff	L-H Ach	H-L Ach	L-H Aff
L-H Pow	1.000	0.304	0.225	0.109	0.073	*0.014*
H-L Pow	0.304	1.000	0.763	0.139	*0.034*	*0.002*
H-L Aff	0.225	0.763	1.000	0.229	0.063	*0.003*
L-H Ach	0.109	0.139	0.229	1.000	0.454	0.157
H-L Ach	0.073	*0.034*	0.063	0.454	1.000	0.624
L-H Aff	*0.014*	*0.002*	*0.003*	0.157	0.624	1.000

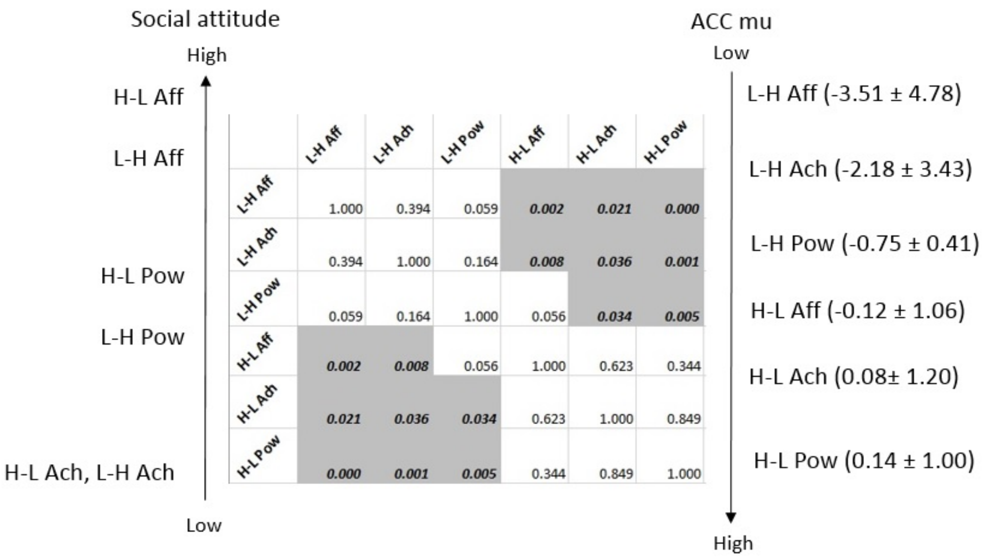
(b) Satisfaction feedback

Figure D.42: Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Random Ruby. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	L-H Pow	H-L Aff	H-L Pow	H-L Ach
L-H Aff	1.000	0.297	***0.000***	***0.000***	***0.000***	***0.000***
L-H Ach	0.297	1.000	***0.001***	***0.000***	***0.000***	***0.000***
L-H Pow	***0.000***	***0.001***	1.000	0.137	***0.044***	***0.011***
H-L Aff	***0.000***	***0.000***	0.137	1.000	0.518	0.083
H-L Pow	***0.000***	***0.000***	***0.044***	0.518	1.000	0.177
H-L Ach	***0.000***	***0.000***	***0.011***	0.083	0.177	1.000

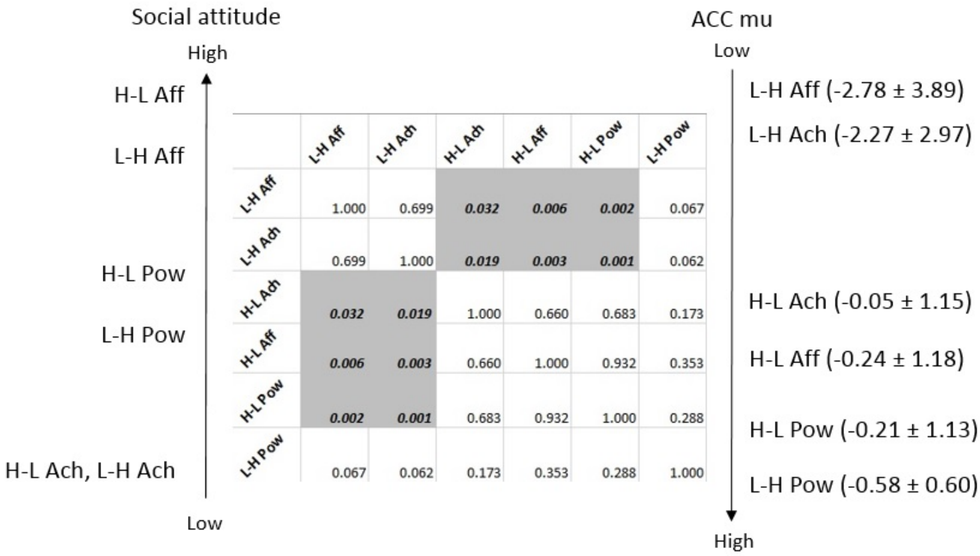
(a) IPP



	L-H Aff	L-H Ach	L-H Pow	H-L Aff	H-L Ach	H-L Pow
L-H Aff	1.000	0.394	0.059	***0.002***	***0.021***	***0.000***
L-H Ach	0.394	1.000	0.164	***0.008***	***0.036***	***0.001***
L-H Pow	0.059	0.164	1.000	0.056	***0.034***	***0.005***
H-L Aff	***0.002***	***0.008***	0.056	1.000	0.623	0.344
H-L Ach	***0.021***	***0.036***	***0.034***	0.623	1.000	0.849
H-L Pow	***0.000***	***0.001***	***0.005***	0.344	0.849	1.000

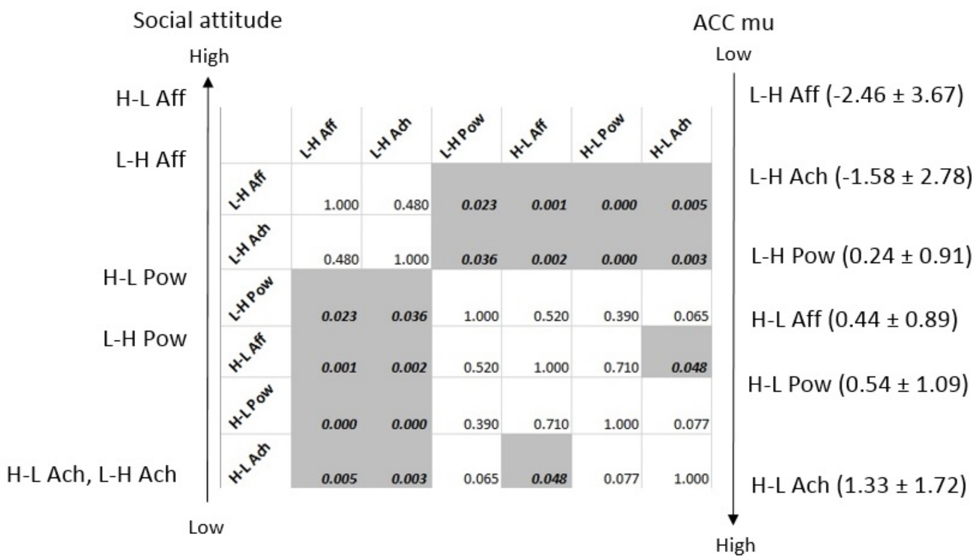
(b) Action

Figure D.43: Results of using ACC mu band in IPP and action to reveal social attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	H-L Ach	H-L Aff	H-L Pow	L-H Pow
L-H Aff	1.000	0.699	*0.032*	*0.006*	*0.002*	0.067
L-H Ach	0.699	1.000	*0.019*	*0.003*	*0.001*	0.062
H-L Ach	*0.032*	*0.019*	1.000	0.660	0.683	0.173
H-L Aff	*0.006*	*0.003*	0.660	1.000	0.932	0.353
H-L Pow	*0.002*	*0.001*	0.683	0.932	1.000	0.288
L-H Pow	0.067	0.062	0.173	0.353	0.288	1.000

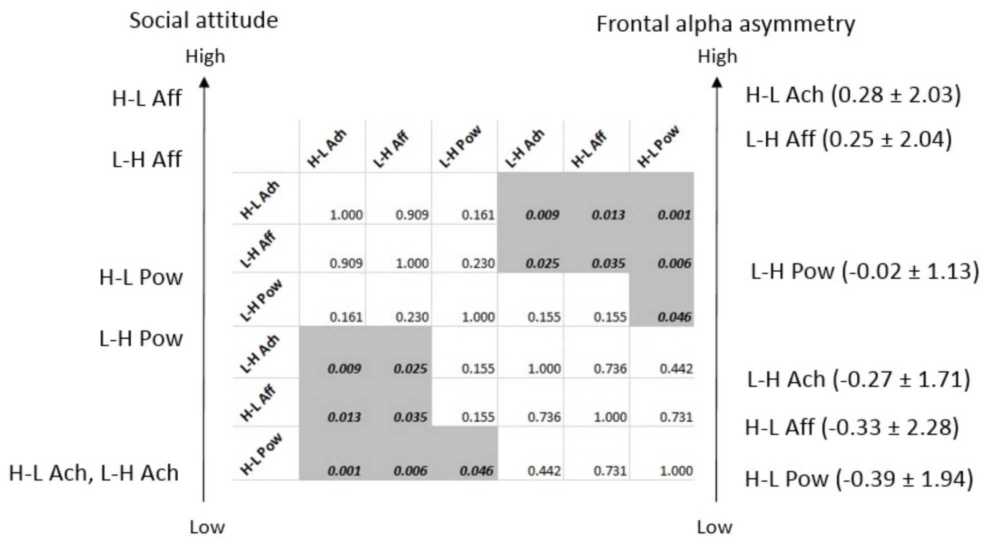
(a) Money feedback



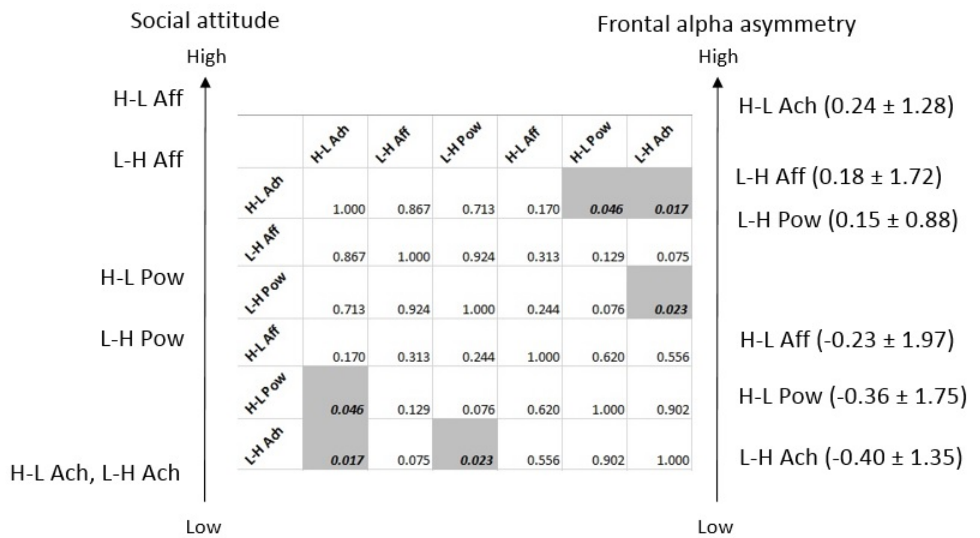
	L-H Aff	L-H Ach	L-H Pow	H-L Aff	H-L Pow	H-L Ach
L-H Aff	1.000	0.480	*0.023*	*0.001*	*0.000*	*0.005*
L-H Ach	0.480	1.000	*0.036*	*0.002*	*0.000*	*0.003*
L-H Pow	*0.023*	*0.036*	1.000	0.520	0.390	0.065
H-L Aff	*0.001*	*0.002*	0.520	1.000	0.710	*0.048*
H-L Pow	*0.000*	*0.000*	0.390	0.710	1.000	0.077
H-L Ach	*0.005*	*0.003*	0.065	*0.048*	0.077	1.000

(b) Satisfaction feedback

Figure D.44: Results of using ACC mu band in money and satisfaction feedback to reveal social attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

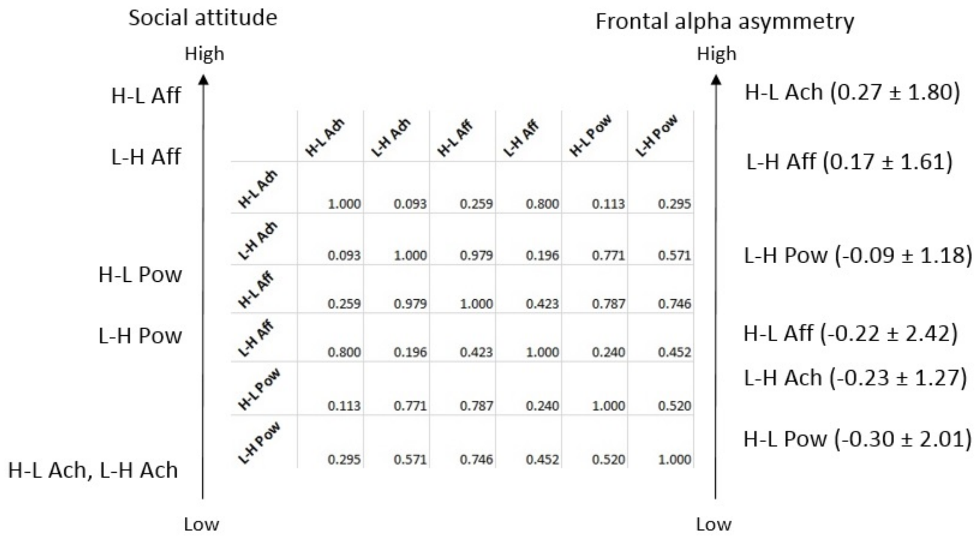


(a) IPP



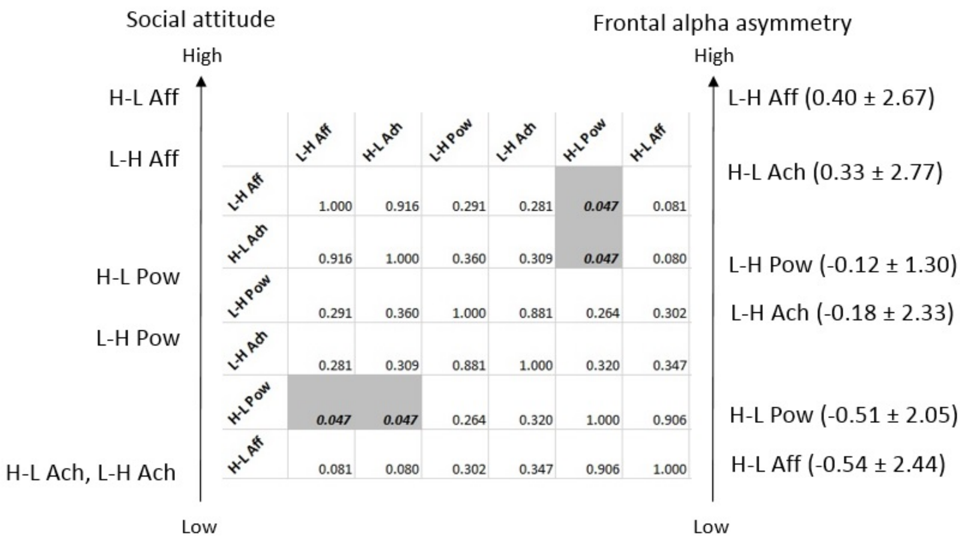
(b) Action

Figure D.45: Results of using frontal alpha asymmetry in IPP and action to reveal social attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.093	0.259	0.800	0.113	0.295
L-H Ach	0.093	1.000	0.979	0.196	0.771	0.571
H-L Aff	0.259	0.979	1.000	0.423	0.787	0.746
L-H Aff	0.800	0.196	0.423	1.000	0.240	0.452
H-L Pow	0.113	0.771	0.787	0.240	1.000	0.520
L-H Pow	0.295	0.571	0.746	0.452	0.520	1.000

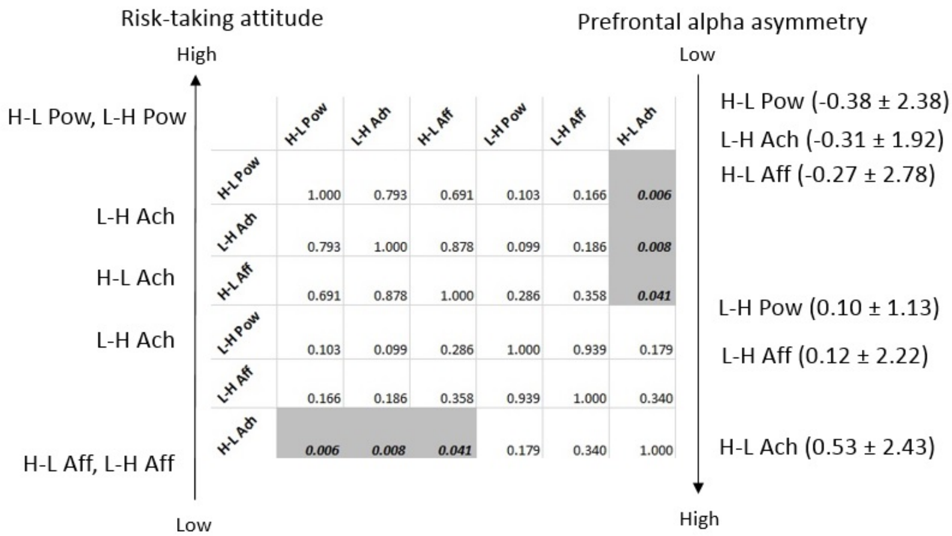
(a) Money feedback



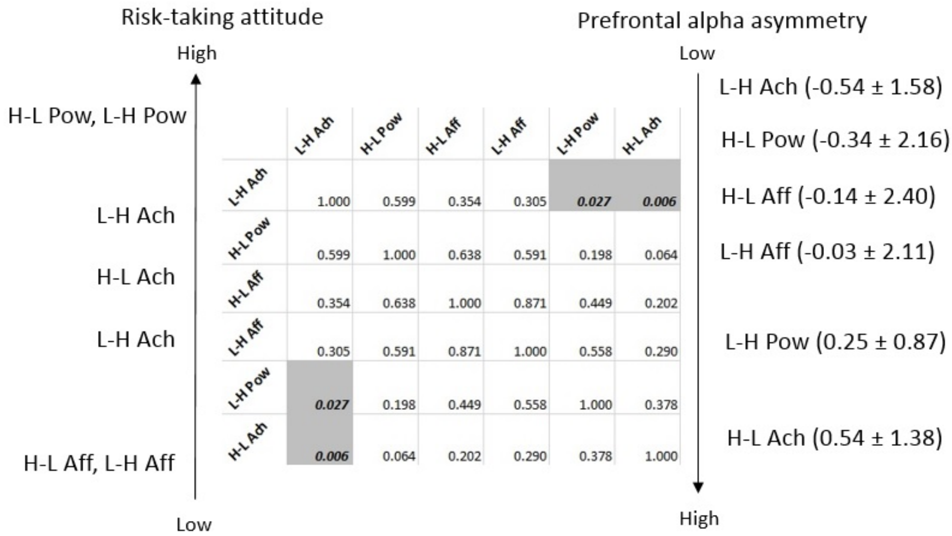
	L-H Aff	H-L Ach	L-H Pow	L-H Ach	H-L Pow	H-L Aff
L-H Aff	1.000	0.916	0.291	0.281	***0.047***	0.081
H-L Ach	0.916	1.000	0.360	0.309	***0.047***	0.080
L-H Pow	0.291	0.360	1.000	0.881	0.264	0.302
L-H Ach	0.281	0.309	0.881	1.000	0.320	0.347
H-L Pow	***0.047***	***0.047***	0.264	0.320	1.000	0.906
H-L Aff	0.081	0.080	0.302	0.347	0.906	1.000

(b) Satisfaction feedback

Figure D.46: Results of using frontal alpha asymmetry in money and satisfaction feedback to reveal social attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

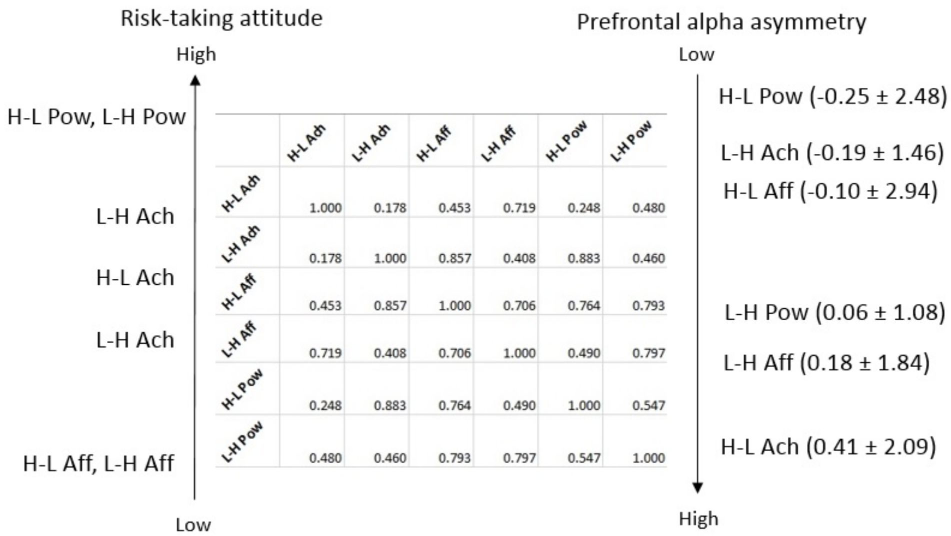


(a) IPP

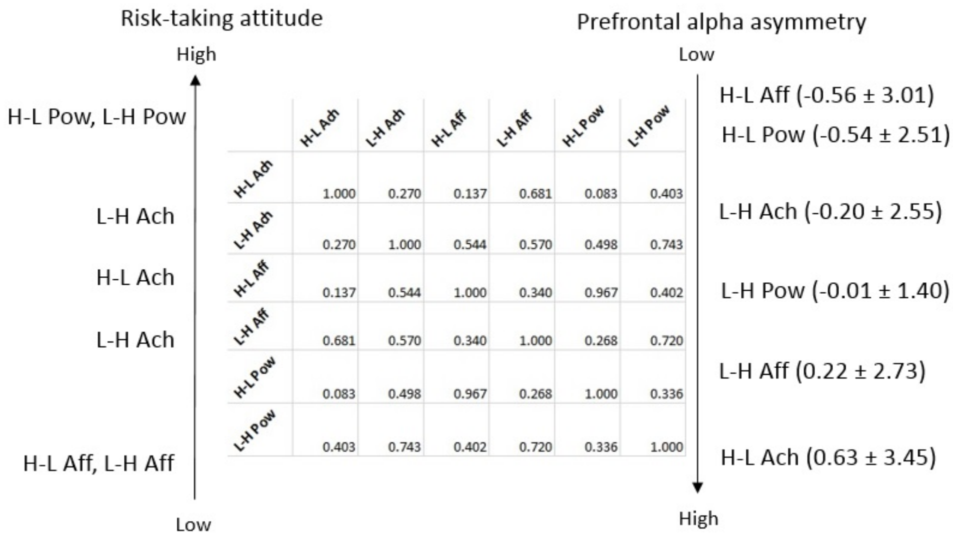


(b) Action

Figure D.47: Results of using prefrontal alpha asymmetry in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

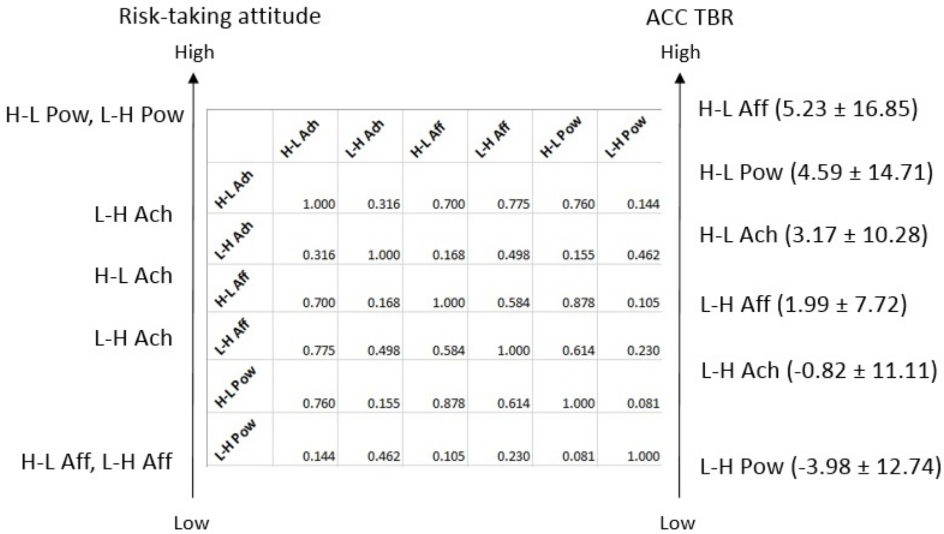


(a) Money feedback



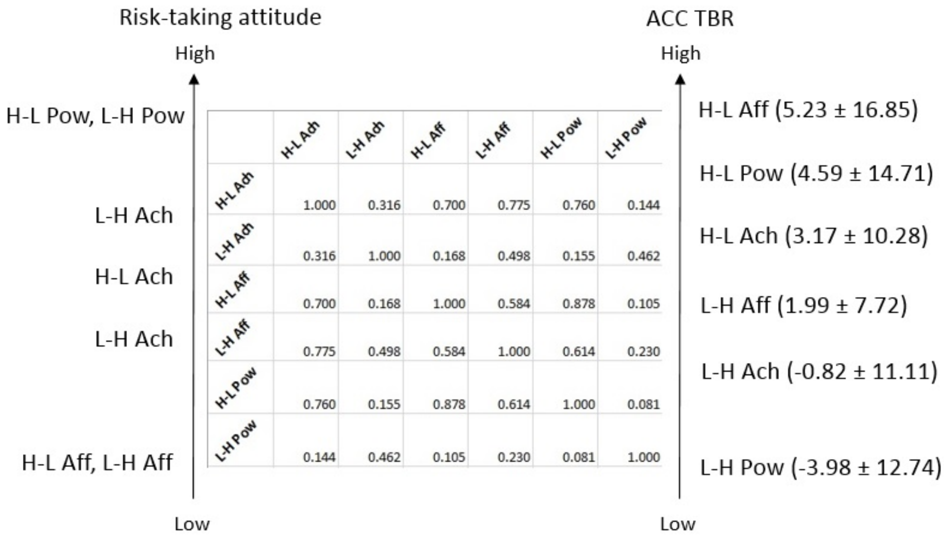
(b) Satisfaction feedback

Figure D.48: Results of using prefrontal alpha asymmetry in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.316	0.700	0.775	0.760	0.144
L-H Ach	0.316	1.000	0.168	0.498	0.155	0.462
H-L Aff	0.700	0.168	1.000	0.584	0.878	0.105
L-H Aff	0.775	0.498	0.584	1.000	0.614	0.230
H-L Pow	0.760	0.155	0.878	0.614	1.000	0.081
L-H Pow	0.144	0.462	0.105	0.230	0.081	1.000

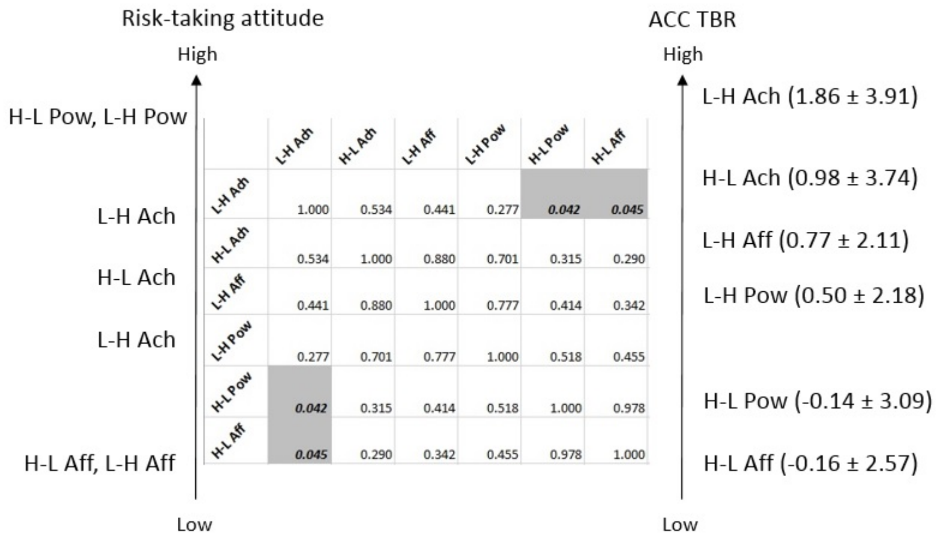
(a) IPP



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.316	0.700	0.775	0.760	0.144
L-H Ach	0.316	1.000	0.168	0.498	0.155	0.462
H-L Aff	0.700	0.168	1.000	0.584	0.878	0.105
L-H Aff	0.775	0.498	0.584	1.000	0.614	0.230
H-L Pow	0.760	0.155	0.878	0.614	1.000	0.081
L-H Pow	0.144	0.462	0.105	0.230	0.081	1.000

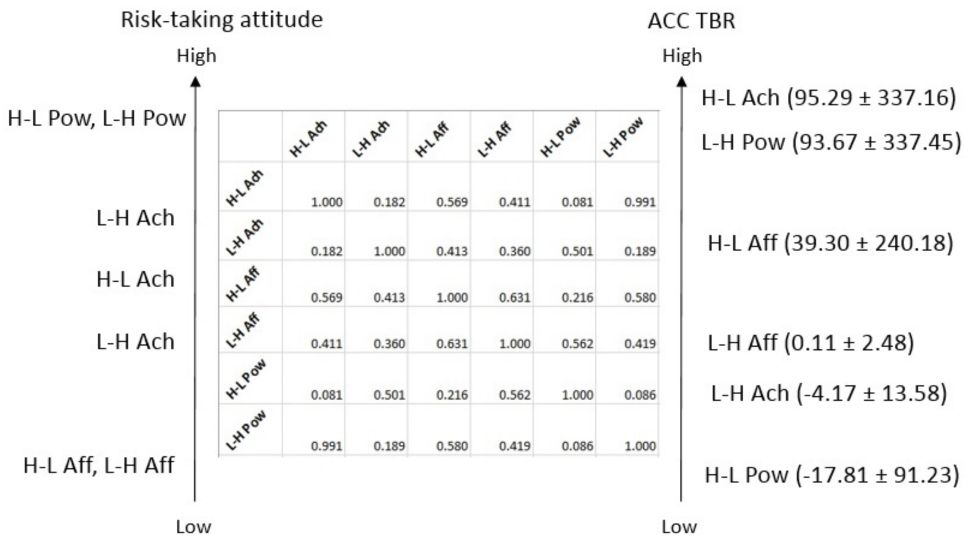
(b) Action

Figure D.49: Results of using ACC theta-beta ratio in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Ach	H-L Ach	L-H Aff	L-H Pow	H-L Pow	H-L Aff
L-H Ach	1.000	0.534	0.441	0.277	***0.042***	***0.045***
H-L Ach	0.534	1.000	0.880	0.701	0.315	0.290
L-H Aff	0.441	0.880	1.000	0.777	0.414	0.342
L-H Pow	0.277	0.701	0.777	1.000	0.518	0.455
H-L Pow	***0.042***	0.315	0.414	0.518	1.000	0.978
H-L Aff	***0.045***	0.290	0.342	0.455	0.978	1.000

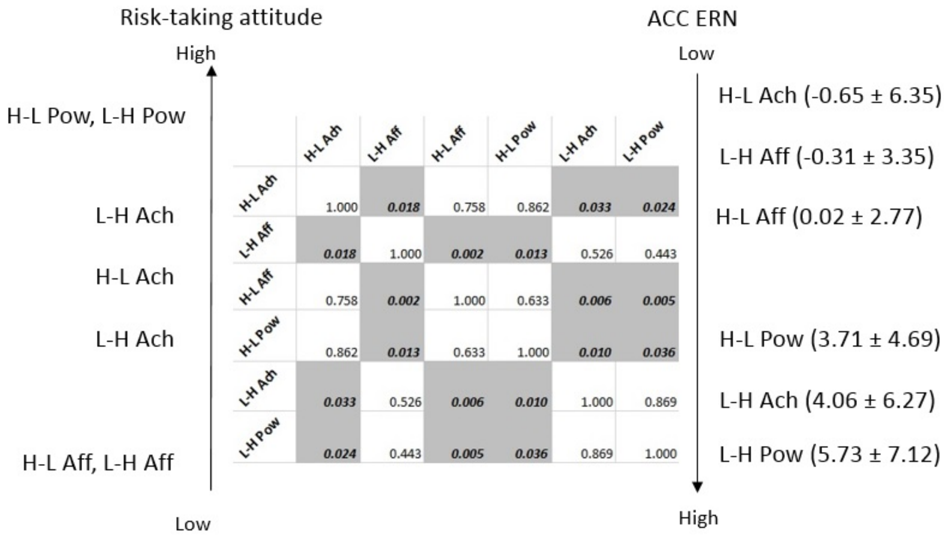
(a) Money feedback



	H-L Ach	L-H Ach	H-L Aff	L-H Aff	H-L Pow	L-H Pow
H-L Ach	1.000	0.182	0.569	0.411	0.081	0.991
L-H Ach	0.182	1.000	0.413	0.360	0.501	0.189
H-L Aff	0.569	0.413	1.000	0.631	0.216	0.580
L-H Aff	0.411	0.360	0.631	1.000	0.562	0.419
H-L Pow	0.081	0.501	0.216	0.562	1.000	0.086
L-H Pow	0.991	0.189	0.580	0.419	0.086	1.000

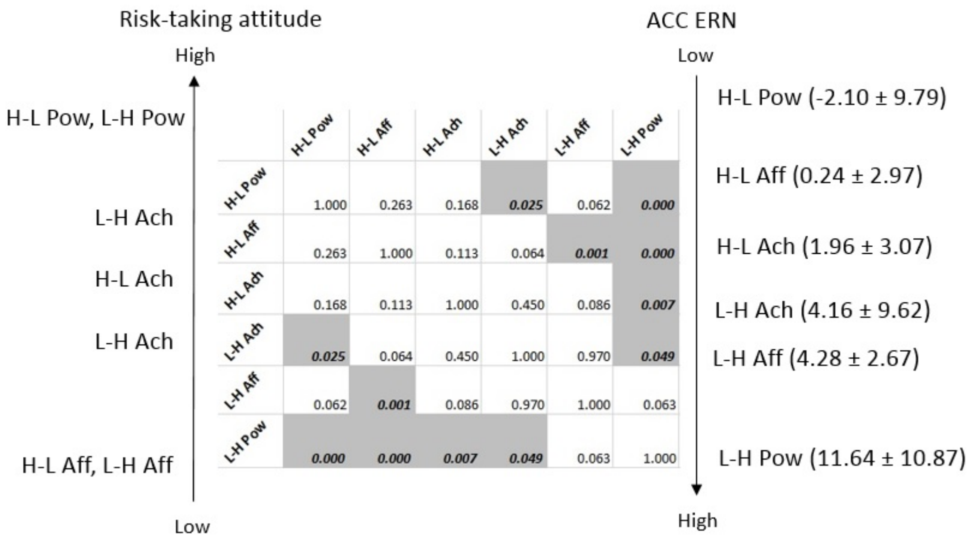
(b) Satisfaction feedback

Figure D.50: Results of using ACC TBR in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Ach	L-H Aff	H-L Aff	H-L Pow	L-H Ach	L-H Pow
H-L Ach	1.000	*0.018*	0.758	0.862	*0.033*	*0.024*
L-H Aff	*0.018*	1.000	*0.002*	*0.013*	0.526	0.443
H-L Aff	0.758	*0.002*	1.000	0.633	*0.006*	*0.005*
H-L Pow	0.862	*0.013*	0.633	1.000	*0.010*	*0.036*
L-H Ach	*0.033*	0.526	*0.006*	*0.010*	1.000	0.869
L-H Pow	*0.024*	0.443	*0.005*	*0.036*	0.869	1.000

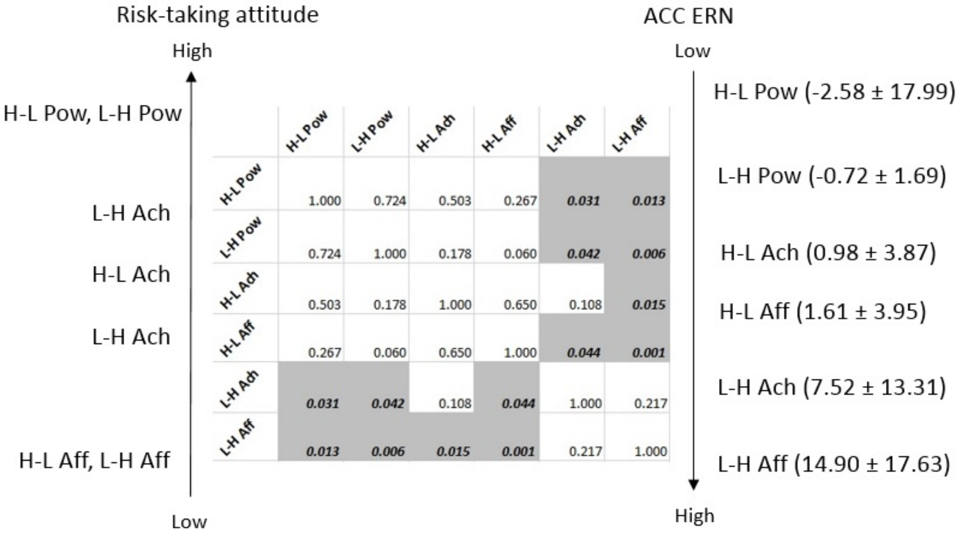
(a) IPP



	H-L Pow	H-L Aff	H-L Ach	L-H Ach	L-H Aff	L-H Pow
H-L Pow	1.000	0.263	0.168	*0.025*	0.062	*0.000*
H-L Aff	0.263	1.000	0.113	0.064	*0.001*	*0.000*
H-L Ach	0.168	0.113	1.000	0.450	0.086	*0.007*
L-H Ach	*0.025*	0.064	0.450	1.000	0.970	*0.049*
L-H Aff	0.062	*0.001*	0.086	0.970	1.000	0.063
L-H Pow	*0.000*	*0.000*	*0.007*	*0.049*	0.063	1.000

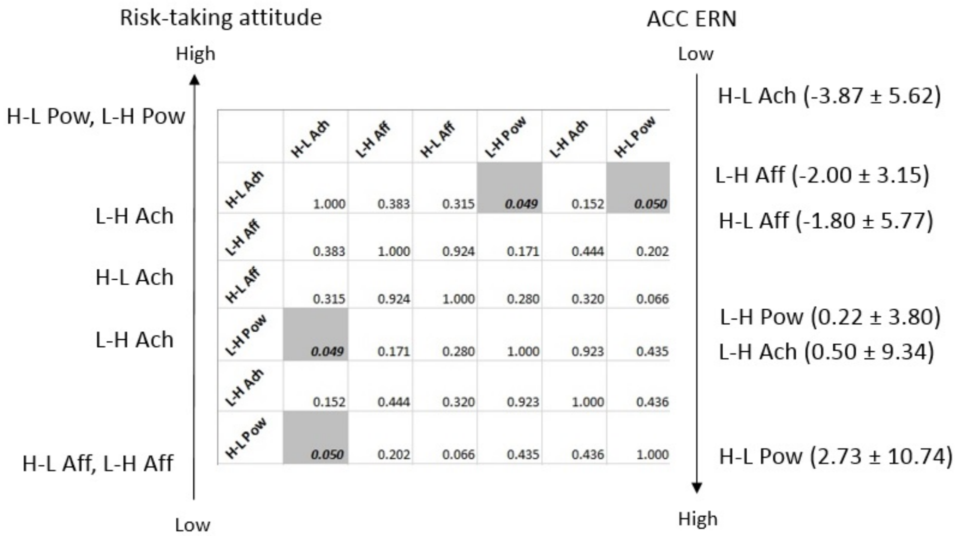
(b) Action

Figure D.51: Results of using ACC ERN in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	H-L Pow	L-H Pow	H-L Ach	H-L Aff	L-H Ach	L-H Aff
H-L Pow	1.000	0.724	0.503	0.267	***0.031***	***0.013***
L-H Pow	0.724	1.000	0.178	0.060	***0.042***	***0.006***
H-L Ach	0.503	0.178	1.000	0.650	0.108	***0.015***
H-L Aff	0.267	0.060	0.650	1.000	***0.044***	***0.001***
L-H Ach	***0.031***	***0.042***	0.108	***0.044***	1.000	0.217
L-H Aff	***0.013***	***0.006***	***0.015***	***0.001***	0.217	1.000

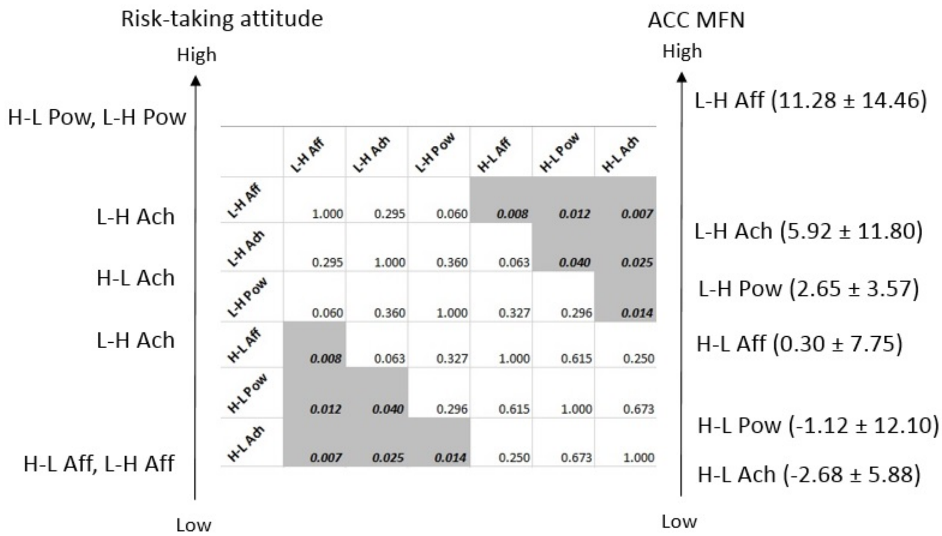
(a) Money feedback



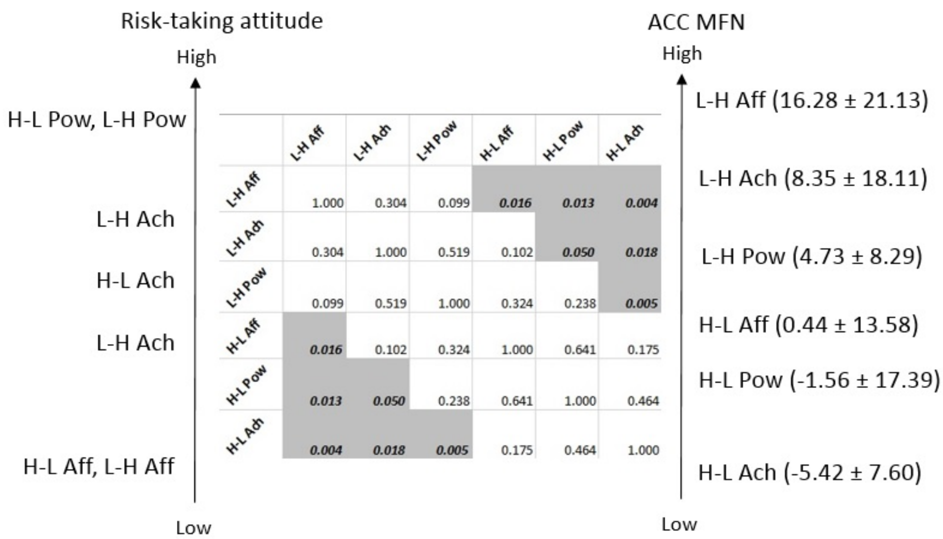
	H-L Ach	L-H Aff	H-L Aff	L-H Pow	L-H Ach	H-L Pow
H-L Ach	1.000	0.383	0.315	***0.049***	0.152	***0.050***
L-H Aff	0.383	1.000	0.924	0.171	0.444	0.202
H-L Aff	0.315	0.924	1.000	0.280	0.320	0.066
L-H Pow	***0.049***	0.171	0.280	1.000	0.923	0.435
L-H Ach	0.152	0.444	0.320	0.923	1.000	0.436
H-L Pow	***0.050***	0.202	0.066	0.435	0.436	1.000

(b) Satisfaction feedback

Figure D.52: Results of using ACC ERN in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

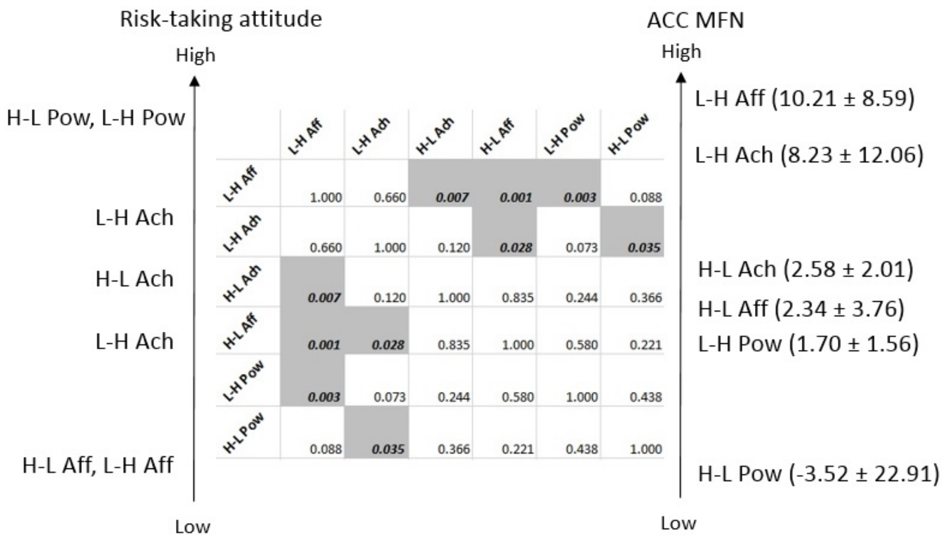


(a) IPP



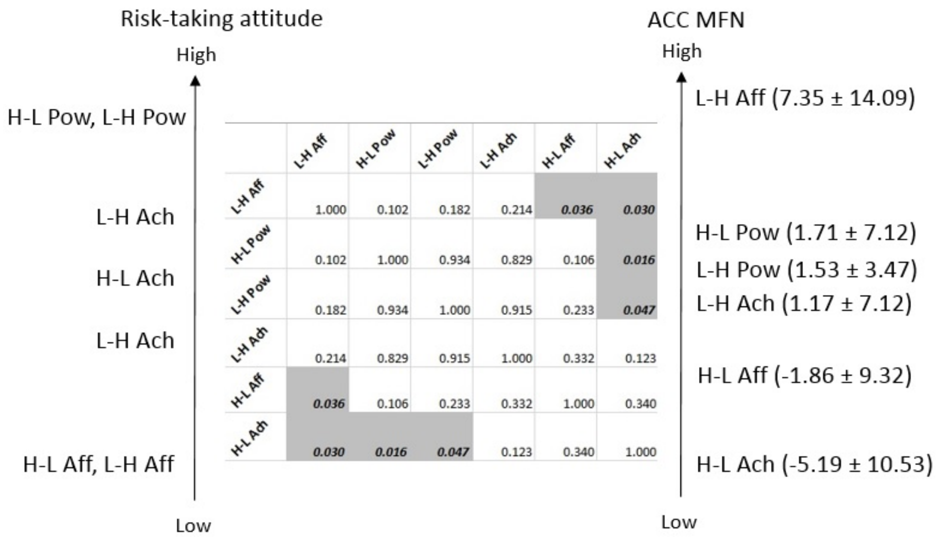
(b) Action

Figure D.53: Results of using ACC MFN in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



	L-H Aff	L-H Ach	H-L Ach	H-L Aff	L-H Pow	H-L Pow
L-H Aff	1.000	0.660	***0.007***	***0.001***	***0.003***	0.088
L-H Ach	0.660	1.000	0.120	***0.028***	0.073	***0.035***
H-L Ach	***0.007***	0.120	1.000	0.835	0.244	0.366
H-L Aff	***0.001***	***0.028***	0.835	1.000	0.580	0.221
L-H Pow	***0.003***	0.073	0.244	0.580	1.000	0.438
H-L Pow	0.088	***0.035***	0.366	0.221	0.438	1.000

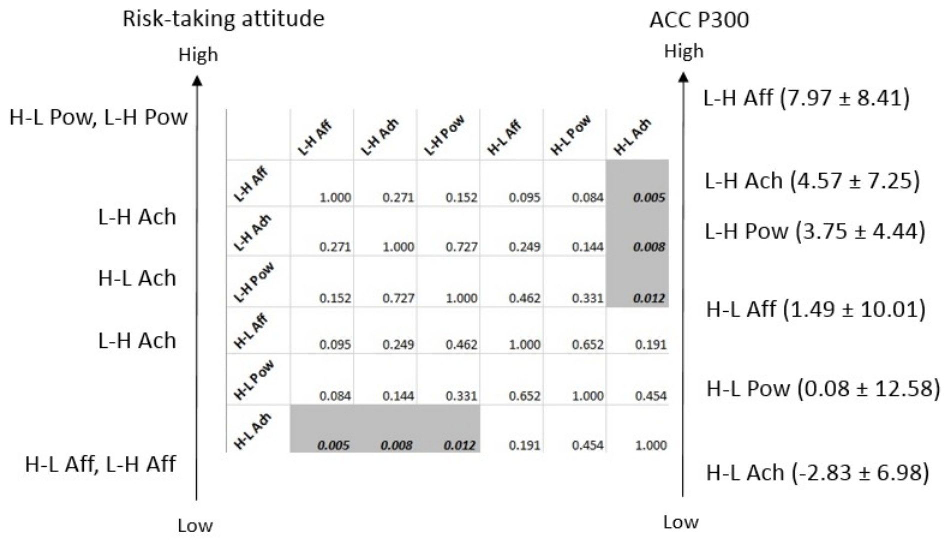
(a) Money feedback



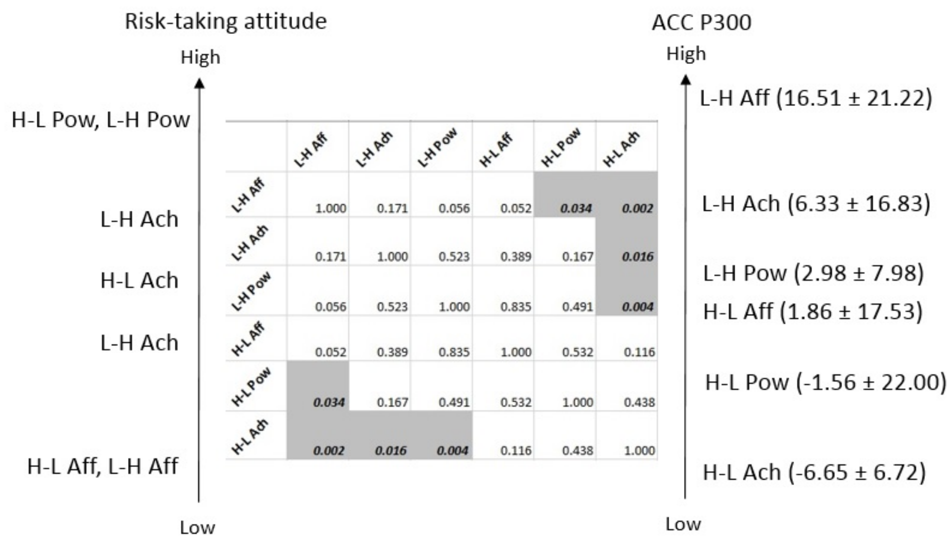
	L-H Aff	H-L Pow	L-H Pow	L-H Ach	H-L Aff	H-L Ach
L-H Aff	1.000	0.102	0.182	0.214	***0.036***	***0.030***
H-L Pow	0.102	1.000	0.934	0.829	0.106	***0.016***
L-H Pow	0.182	0.934	1.000	0.915	0.233	***0.047***
L-H Ach	0.214	0.829	0.915	1.000	0.332	0.123
H-L Aff	***0.036***	0.106	0.233	0.332	1.000	0.340
H-L Ach	***0.030***	***0.016***	***0.047***	0.123	0.340	1.000

(b) Satisfaction feedback

Figure D.54: Results of using ACC MFN in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

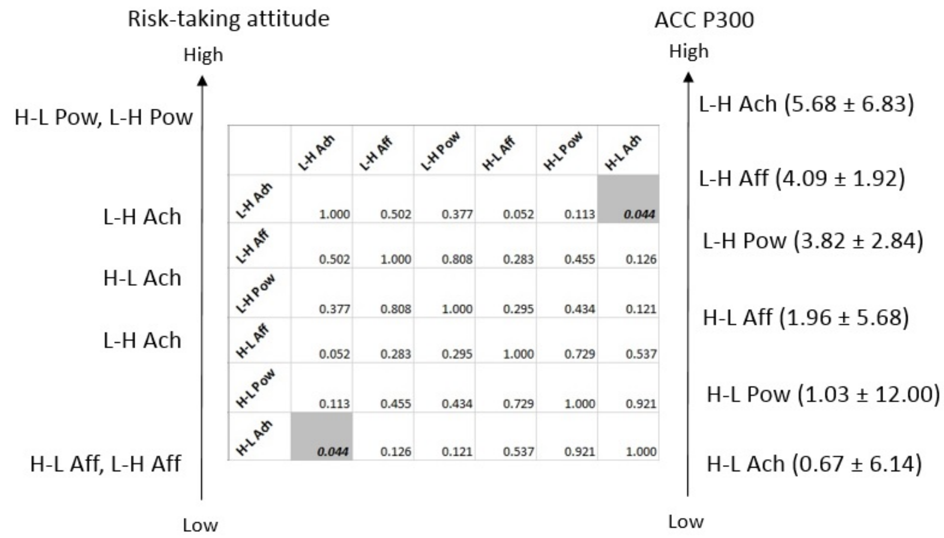


(a) IPP

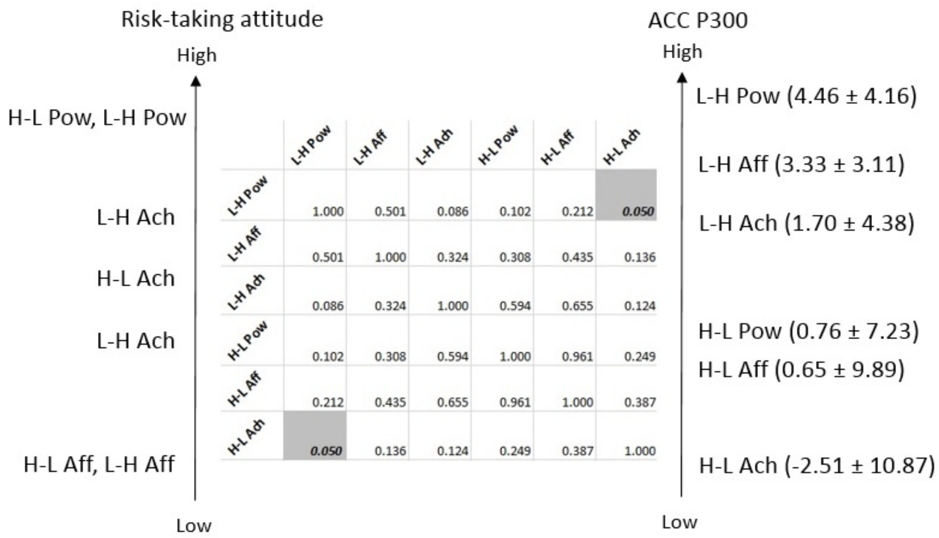


(b) Action

Figure D.55: Results of using ACC P300 in IPP and action to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.



(a) Money feedback



(b) Satisfaction feedback

Figure D.56: Results of using ACC P300 in money and satisfaction feedback to reveal risk-taking attitude when playing with Vengeful Vince. The p-value of independent t-test between hope and fear components of each motivation is presented.

Appendix E

An Experiment that Compares Feature Selection Methods

E.1 Aim

The aim of this experiment is to compare different feature selection techniques for identifying achievement, affiliation and power motivation. Three feature selection methods are compared in this experiment to classify motivation using EEG signal.

E.2 Method

The chi-squared test is a statistical hypothesis test for determining whether there is a significant difference between the distribution of two variables. Chi-square attribute evaluation method evaluates the attribute by computing the value of the chi-squared statistic with respect to the class. A higher chi-square value indicates a higher correlation between this feature and the class. The features are ranked according to the evaluation metrics. The first ten highest features are selected for further classification.

Correlation subset evaluation method evaluates a subset of features by considering

Table E.1: Summary of the most effective EEG features for achievement motivation using three feature selection methods in IPP

Achievement	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	Oz_mean	FT8_γ, AF8_γ, AF6_γ	TP7_θ, PO1_α, C2_θ, F5_θ	F1_γ, F3_α,
Correlation subset evaluation		AF8_γ, AF6_γ	F5_θ, C5_θ, TP7_θ	F3_α, F1_γ
Wrapper subset evaluation	PO4_mean, Oz_peak	Cz_θ, C1_α		F3_α, PO3_γ

each feature together with the degree of redundancy between variables [160]. In this method, subsets of features that are highly correlated with the class and low inter-correlation are selected. It employs the best-first searching approach that searches the feature subset by greedy hill-climbing augmented with a backtracking facility.

Wrapper subset evaluation method incorporates a machine learning classifier to evaluate feature subset [166]. Five-fold cross validation is used to estimate the accuracy of the classifier using a subset of features. The setting of KNN is that the number of neighbours is 3 and euclidean distance is employed as nearest neighbour searching algorithm. The searching approach for selection feature subset also employs the best-first method that searches the feature subset by greedy hill-climbing together with a backtracking facility.

E.3 Results

This section presents the feature selection performance using EEG signals from the IPP and SNP. Three feature selection methods are compared and EEG features selected for achievement, affiliation and power motivation are discussed.

E.3.1 Individual Play Phase

Tab. E.1, Tab. E.2 and Tab. E.3 show selected EEG features for achievement, affiliation and power motivation using three different feature selection methods re-

Table E.2: Summary of the most effective EEG features for affiliation motivation using three feature selection methods in IPP

Affiliation	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	AF6_mean, FCz_mean, F4_mean	FC2_γ, FC5_γ	POO8_γ	FC5_α, PO7_α, PO5_γ, POO7_γ
Correlation subset evaluation	AF6_mean, F4_mean	FC2_γ	Fz_γ, POO8_γ	F5_δ, FC5_δ, FC5_α, PO7_α, PO1_α, AF1_β, PO1_β, POO7_β, FC3_γ
Wrapper subset evaluation	FCz_mean	CP1_δ, PO4_θ		

Table E.3: Summary of the most effective EEG features for power motivation using three feature selection methods in IPP

Power	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	C5_SD, C5_peak	Oz_δ, C5_γ, AF6_δ, C5_α, C5_θ, C5_δ		C5_δ, F3_δ
Correlation subset evaluation	F2_peak	AF6_δ, FT7_δ, C5_δ, Oz_δ, C5_θ, AF7_α, FPz_α, C5_α, C5_γ, PO8_γ		F3_delta, C5_delta, TP7_θ, FC3_γ, C1_γ
Wrapper subset evaluation		CP3_δ, CP6_δ, Oz_α	PO4_β	

Table E.4: Summary of the most effective EEG features for achievement motivation using three feature selection methods in SNP

Achievement	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	C3_mean, FT7_mean, F2_SD, CP3_mean, F8_mean, F7_peak	F8_δ	TP7_β, CPz_β, F8_δ	
Correlation subset evaluation	AF6_mean, F7_mean, FT7_mean, C3_mean, CP3_mean, CPz_mean	F8_δ, FC4_α	F8_δ, PO1_θ, AF4_δ, TP7_β, POO7_β	FC3_α, C3_β
Wrapper subset evaluation		AFP5_δ, FC6_θ, AF2_γ		

spectively. In IPP, we can see that the wrapper subset evaluation method selects fewer features than chi-square attribute evaluation and correlation subset evaluation. In addition, there are several overlapping features for chi-square attribute evaluation and correlation subset evaluation. However, features selected from the wrapper subset evaluation are different from the other two methods in most cases.

Table E.5: Summary of the most effective EEG features for affiliation motivation using three feature selection methods in SNP

Affiliation	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	PO8_peak	FP2_β, AF7_θ, FC2_δ	POO8_γ	AF7_δ, AFP5_δ, FP1_δ, AF5_δ, AF3_δ
Correlation subset evaluation		FC2_δ, AF7_θ, FP2_β		
Wrapper subset evaluation		CP6_δ, CP6_θ, FC1_β		POO7_γ

Table E.6: Summary of the most effective EEG features for power motivation using three feature selection methods in SNP

Power	***Temporal***	***Spectral***	***Time-frequency***	***Asymmetry***
Chi-square attribute evaluation	TP8_mean, C1_mean	FT7_θ, C5_β, FC3_β, FC6_β, F2_β, T8_β, C6_β	PO5_α	
Correlation subset evaluation	C1_mean, TP8_mean, F7_peak	FT7_θ, F2_β	AF2_δ, PO5_α, CP5_β, CP6_γ	O1_δ
Wrapper subset evaluation TP8_mean		POO8_δ, FP1_α, PO5_α, POz_α, CP5_β		

Table E.7: Performance of player motivation classification using three different feature selection methods in IPP

Feature selection	***Achievement***	***Affiliation***	***Power***
Chi-square attribute evaluation	64% ± 22%	72% ± 17%	75% ± 17%
Correlation subset evaluation	68% ± 19%	80% ± 16%	71% ± 20%
Wrapper subset evaluation	84% ± 18%	81% ± 15%	76% ± 18%

Table E.8: Performance of player motivation classification using three different feature selection methods in SNP

Feature selection	***Achievement***	***Affiliation***	***Power***
Chi-square attribute evaluation	54% ± 26%	62% ± 20%	60% ± 21%
Correlation subset evaluation	72% ± 22%	71% ± 23%	77% ± 22%
Wrapper subset evaluation	78% ± 20%	69% ± 25%	92% ± 13%

E.3.2 Social Network Phase

Tab. E.4, Tab. E.5 and Tab. E.6 present EEG features selected for achievement, affiliation and power motivation using the three feature selection methods individually. As for SNP, we also see that there are common EEG features between chi-square attribute evaluation and correlation subset evaluation. Also, fewer EEG features are selected from wrapper subset evaluation and mainly belong to spectral feature type.

As shown in Tab. E.7 and Tab. E.8, the classification accuracies between correlation subset evaluation method and wrapper subset evaluation are similar. Therefore, we believe that features selected from correlation subset evaluation better express the underlying brain activity and are useful for motivation classification.

E.4 Conclusion

Based on the results obtained from three different feature selection methods, we conclude that the correlation subset evaluation method is the most appropriate choice for selecting features for further motivation classification.

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