



Cátia Filipa Mata Cepeda de Vela Bastos

Master of Science in Biomedical Engineering

**Personality Assessment Using Biosignals and
Human Computer Interaction applied to Medical
Decision Making**

Thesis submitted in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy in
Biomedical Engineering

Adviser: Hugo Filipe Silveira Gamboa,
Assistant Professor, NOVA University of Lisbon

Co-adviser: Marcus Cheetham,
Senior Research Associate, University Hospital of
Zurich

Examination Committee

Chairperson: Professor José Paulo Moreira dos Santos
Raporteurs: Professor Federico Antonio Niccolo Amadeo Cabitza
Professor Sergi Bermúdez i Badia
Members: Professor José Paulo Moreira dos Santos
Professor João Manuel Monteiro da Silva Moreira
Professor Hugo Filipe Silveira Gamboa

Personality Assessment Using Biosignals and Human Computer Interaction applied to Medical Decision Making

Copyright © Cátia Filipa Mata Cepeda de Vela Bastos, Faculty of Sciences and Technology, NOVA University Lisbon.

The Faculty of Sciences and Technology and the NOVA University Lisbon have the right, perpetual and without geographical boundaries, to file and publish this dissertation through printed copies reproduced on paper or on digital form, or by any other means known or that may be invented, and to disseminate through scientific repositories and admit its copying and distribution for non-commercial, educational or research purposes, as long as credit is given to the author and editor.

"Believe you can and you're halfway there."

Theodore Roosevelt

ACKNOWLEDGEMENTS

This thesis document is the final result of a long period of work. This PhD would not be possible without the contribution and collaboration of many remarkable people that allowed me to grow professionally and personally.

I would like to first thank professor Hugo. As my professor in the first year of college, he told me that the funny part of being a biomedical engineer is that we cannot imagine the amount of possible fields it can cover. Some years later, professor Hugo introduced me a master thesis that, as he said, it was just like me. It was a collaboration with psychologists, a field that I could never thought it could have a relationship with biomedical engineering. After all this, he had supervised my PhD thesis for four years. A big thanks for always guiding and supporting all my academic progress. As a supervisor, more than providing the technical support, he was also responsible for my growth in terms of soft skills, by trusting me and giving me the freedom to make all the final decisions.

To Marcus Cheetham, for welcoming me in Zurich and introducing me in an environment of psychologists and medical doctors. Even from a totally different field, he was always available to hear my ideas related to psychology topics and also interested in understanding how worked the engineering part of this thesis. Marcus was also responsible for dealing with the preparation of the studies regarded, making possible the large data set of this thesis. He also helped me to improve my writing skills, by revising the academic documents prepared.

Thank to University Hospital of Zurich and to Portuguese National Funding Agency FCT for the financing support. To PLUX - Wireless Biosignals, S.A that managed the collaboration with Zurich and provided the biosignals acquisition system. To the Department of Psychology of the University of Zurich and to the University Hospital of Zurich that provided the rooms, eye-tracking system and subjects needed to perform our studies. To the Physics Department of the FCT-UNL, that allowed me to learn how to share some knowledge by teaching physics.

Thanks to Maria Camila Dias e Beatriz Esteves, whose master thesis I had the pleasure to coordinate. Their motivation and ideas were contributed to the final results of this thesis.

I would like to thank all the Multimorbidity and Complexity Research Group for the experience of working in such a multidisciplinary team, with whom I could participate in interesting collaborative projects. Thanks to Dina, to the master students and Saara,

that were responsible for the studies execution.

This PhD also gave me a friend for life. Even from another country and for a different field, I am grateful to share the life-experience of making a PhD with Dina. Marcus defined us as "a crazy couple" because, with all the difficulties and frustrations that sometimes we experienced, we were always laughing and having fun while hard working. Together or 2000 km away, we make a great team. Thank you for taking care of the acquisitions' documentation and executions. Moreover, thanks for welcoming me in Zurich and, for more than being a great team mate, being such a good friend.

Talking about friends, I cannot forget the Libphys team. They were, for sure, a huge contribution in all this process. It was certainly a good reason in bad days to go to the lab and find João, David, Daniel and more recently Nafiseh and Ricardo. They were always available for hearing my problems, for inspiring me and to brainstorm in the white board to discuss new ideas and find solutions. Thanks for all the collaborations, your support, patient and friendship. Behind the wall but not forgotten, a special thanks to Andreia, Paulo and Jorge for the daily breaks and partnership.

To my dear friends Mariana, Joaquina, Vila Verde, Joana Raquel, Maria, Raquel and Zoio. Even with some spatial distance, you were always there for the good and the bad as part of my family.

To Rodrigo that, during the last years, dealt with my problems and was obliged to share our time with my thesis. Thanks for your patience and for encourage me in the hardest moments. I am very proud of our personal and professional growth during the last 10 years. I know that, together, we'll go further. I am grateful to have you in my life.

My biggest thank you go to my parents, sister and brother. Without them, nothing of this would be possible because they made me what I am today. Thanks for teaching me that everything is possible and that there is a solution for everything in life. Thanks for your help and support in everything of my life and for always believing in me.

ABSTRACT

Clinical decision-making for patients with multiple acute or chronic diseases (i.e. multimorbidity) is complex. There is often no 'right' or optimal treatment due to the potentially harmful effects of multiple interactions between drugs and diseases. This makes it necessary to establish trade-offs between the benefits and risks of different treatment strategies. This means also that there may be high levels of risk and uncertainty when making decisions. One factor that can influence how decisions are made under conditions of risk and uncertainty is the decision maker's personality. The studies of this dissertation used biosignals and eye-tracking methods and developed pointer tracking techniques to monitor human computer interaction to assess, using machine learning techniques, the individual personality of decision makers.

Data acquisition systems were designed and prepared to collect and synchronize: 1) physiological data - electrocardiogram, blood volume pulse and electrodermal activity; 2) human-computer interaction data - pointer movements, eye tracking and pupil diameter; 3) decision-making task data; and 4) personality questionnaire' results. A set of processing tools was developed to ensure the correct extraction of psychophysiology-related features that could manifest personality. These features were combined by several machine learning algorithms to predict the Big-Five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness and Conscientiousness.

The five personality traits were well modelled by, at least, one of the sets of features extracted. With a sample of 88 students, features from the pointer movements in online surveys predicted four personality traits with a mean squared error (MSE) <0.46 . The blood volume pulse responses in a decision-making task trained in a distinct sample of 79 students predicted four personality traits with a MSE <0.49 . The application of the personality models based on the pointer movements in the personality questionnaire in a sample of 12 medical doctors achieved a MSE <0.40 for three personality traits. These were the best results achieved in each context of this thesis.

The outcomes of this work demonstrate the huge potential of broader models that predict personality through human behaviour, with possible application in a wide variety of fields, such as human resources, medical research studies or machine learning approaches.

Keywords: Biosignals, Human-Computer Interaction, Knowledge Extraction, Psychophysiology, Personality, Machine Learning Algorithms, Medical Decision-Making

RESUMO

A tomada de decisão clínica para pacientes com múltiplas doenças agudas ou crónicas (i.e., multimorbidade) é complexa. Normalmente, não existe um tratamento 'certo' ou ideal devido aos efeitos potencialmente prejudiciais das interacções entre medicamentos e doenças. Torna-se assim necessário estabelecer um compromisso entre os benefícios e riscos de diferentes tratamentos, podendo haver altos níveis de risco e incerteza ao tomar decisões. Um factor que pode influenciar a forma como estas decisões são tomadas é a personalidade de quem toma a decisão. Os estudos desta dissertação utilizaram biosinais, métodos de monitorização ocular e desenvolveram técnicas de monitorização do rato para analisar a interacção homem-máquina (IHM) por forma a avaliar, usando técnicas de aprendizagem automática, a personalidade do indivíduo que toma a decisão.

Sistemas de aquisição de dados foram preparados para recolher e sincronizar: 1) dados fisiológicos - electrocardiograma, onda de pulso e actividade electrodérmica; 2) dados de IHM - movimentos do rato (MR), movimento ocular e diâmetro da pupila; 3) dados da tomada de decisão; e 4) resultados do questionário de personalidade. Um conjunto de ferramentas de processamento são desenvolvidas para garantir a extracção de variáveis que poderão manifestar personalidade. Estas foram combinadas por diversos algoritmos de aprendizagem automática para prever os cinco grandes traços de personalidade: Abertura para a experiência, Conscienciosidade, Extroversão, Amabilidade e Neuroticismo.

A modelação de cada traço de personalidade foi conseguida por, pelo menos, um dos conjuntos de variáveis. Com uma amostra de 88 estudantes, as características do MR em questionários preveram quatro traços de personalidade com um erro quadrático médio (EQM) <0.46 . As respostas da onda de pulso em tarefas de tomada de decisão numa amostra distinta de 79 estudantes preveram quatro traços com um EQM <0.49 . Para uma amostra de 12 médicos, a aplicação dos modelos baseados nos MR no questionário de personalidade obteve um EQM <0.40 para três traços. Estes foram os melhores resultados obtidos para cada contexto desta tese.

Os resultados deste trabalho demonstram o grande potencial de modelos mais abrangentes que prevejam personalidade através do comportamento humano, com possível aplicação numa grande variedade de domínios, tais como recursos humanos, investigação médica ou soluções com aprendizagem automática.

Palavras-chave: Biosinais, Interação homem-máquina, Extração de Informação, Psicofisiologia, Personalidade, Algoritmos de Aprendizagem Automática, Tomada de Decisão Médica

CONTENTS

List of Figures	xvii
List of Tables	xxi
Acronyms	xxv
1 Motivation	1
1.1 Background	1
1.2 Relevance	1
1.3 The present research question	3
1.4 Thesis Structure	4
2 Theoretical Concepts	7
2.1 Physiological Signals	7
2.1.1 Nervous System	9
2.1.2 Electrocardiogram	10
2.1.3 Electrodermal activity	11
2.1.4 Blood Volume Pulse	14
2.2 Human-Computer Interaction	16
2.2.1 Eye Tracker	16
2.2.2 Pointer Tracker	18
2.3 Decision Making	19
2.3.1 Medical Decision Making	20
2.4 Personality	20
2.4.1 Five Factor Personality	22
3 State of the art	25
3.1 Human behaviour analysis from physiological signals	25
3.2 Human behaviour analysis from human-computer interaction	28
3.3 Human behaviour analysis from decision-making tasks	30
3.4 Human behaviour analysis from medical decision-making tasks	31
3.5 Conclusion	31
4 Data Management	33

CONTENTS

4.1	Data Acquisition	33
4.1.1	Decision-Making Task	34
4.1.2	Online Surveys	39
4.2	Scientific Computation	41
4.3	Studies Design	42
4.3.1	Study 1: Online questionnaires in an uncontrolled environment	42
4.3.2	Study 2: Simulated Decision Making Task	43
4.3.3	Study 3: Simulated Decision Making Task with Psychophysiological Data Record	43
4.3.4	Study 4: Medical Decision Making Task	44
5	Technical Tools	45
5.1	Survey Pointer Processing Tools	45
5.1.1	Interaction Sequence for Questionnaires	46
5.1.2	Pre-processing Data	47
5.1.3	Spatial-temporal Information	49
5.1.4	Micro-behaviours Information	53
5.1.5	Uncertainty Detection	59
5.2	Decision-making Task Processing Tools	61
5.3	Decision-making Task Mouse Processing Tools	61
5.4	Pupil Processing Tools	63
5.5	Electrocardiogram	64
5.6	Blood Volume Pulse	67
5.7	Electrodermal Activity	67
6	Modelling Personality using Machine Learning	73
6.1	Machine learning algorithms	73
6.1.1	Feature selection	75
6.1.2	Model training	76
6.1.3	Model evaluation	79
6.2	Personality baseline	80
6.3	Modelling personality results	82
6.3.1	Model based on survey mouse features	83
6.3.2	Model based on decision-making task features	89
6.3.3	Model based on decision-making task mouse features	96
6.3.4	Model based on pupil features	98
6.3.5	Model based on electrocardiogram features	100
6.3.6	Model based on blood volume pulse features	104
6.3.7	Model based on electrodermal activity features	108
6.3.8	Model based on biosignals features	113
7	Application in medical decision-making	121

7.1	Personality results	121
7.2	Model Application to MISI	123
8	Conclusions	127
8.1	Overall Results	127
8.2	Contributions	130
8.2.1	List of publications	131
8.3	Application Scenarios	133
8.4	Future Work	133
8.4.1	Extend the research	133
8.4.2	Balance between interpretability and accuracy	134
8.4.3	Support medical decision-making	134
8.4.4	Beyond personality	134
8.5	Future Implications	134
	Bibliography	137
A	Thesis Overview	169
B	Response Uncertainty Model	171
B.1	Introduction	171
B.2	Methods	172
B.2.1	Features Extraction	172
B.2.2	Features Selection	173
B.2.3	Model Training and Testing	173
B.2.4	Classification	174
B.2.5	Model Evaluation	174
B.3	Results and Discussion	175
B.3.1	Model Evaluation	176
C	Personality Questionnaire Procedure	179
D	MISI II Procedure	187

LIST OF FIGURES

1.1	Distribution of diagnoses per inpatient in different age groups of a major city hospital. The in-hospital patient sample is predominantly multimorbid, with MM increasing with age (adapted from [71]).	2
1.2	Thesis structure.	4
2.1	Signal acquisition and processing steps. Based on [106].	9
2.2	In (a) is represented a unique cycle of the ideal ECG and in (b) is represented four cycles with different R-R interval. From [99].	10
2.3	Diagram of eccrine sweat gland. From [92].	13
2.4	Example of an Electrodermal Activity (EDA) signal.	13
2.5	Illustration of a typical Skin Conductance Response (SCR). t_0 corresponds to the onset of the SCR, t_{max} the instant where the maximum value is reached and t_{half} the instant where the SCR returned to half of its maximum amplitude. From [92].	14
2.6	Illustration of a typical Blood Volume Pulse (BVP) wave, with Alternating Current (AC) and Direct Current (DC) components identified. From [7].	15
2.7	Illustration of a typical BVP pulse, with anacrotic and catacrotic phases identified.	16
2.8	Eye anatomy. From [233].	17
2.9	Example of a pupil reflex to light stimulus. L.P. is Latent Period. From [233].	18
4.1	Purpose and outputs of the "Data Management" chapter in this thesis.	33
4.2	Experiment systems connection and synchronization.	34
4.3	IOWA Gambling Task (IGT) schematic representation of the sequential phases of each trial and respective durations. The total game was divided into 5 different blocks, each one with 20 trials. A trial was composed by four phases, the fixation, the choice while the subject is deciding the deck he/she want to select, the anticipation phase to present the deck selected and, finally, the feedback with the monetary win, loss and the current money.	35
4.4	Example of questions with more text transparency when not hovered.	39
4.5	Architecture of online surveys data acquisition.	39
4.6	Sequence of steps in the survey.	43
4.7	Sequence of steps in the Multimorbidity Interaction Severity Index (MISI).	44

5.1	Details about what will be explained and what are the outputs of the Chapter "Technical Tools" in the context of this thesis.	45
5.2	Survey diagram.	46
5.3	Question Group diagram.	47
5.4	Go to question diagram.	47
5.5	Answer question diagram.	47
5.6	Submit diagram.	47
5.7	Spatial signal x-y representation in pixels. The orange dots (●) represent the signal extracted from the pointer movement, the blue dots (○) represent the signal with constant spacing and the black line (-) represent the curve from interpolation.	50
5.8	In the graphic at left it is represented the angles in radians over distance in pixels and the graphic at right represent the curvature in radians/pixels over distance in pixels.	51
5.9	Temporal signal x-y representation in pixels. The orange dots (●) represent the signal extracted from the mouse movement, the blue dots (○) represent the signal with constant and defined spacing and the black line (-) represent the curve from interpolation.	52
5.10	Representation of the y-axis of the pointer movement over time. The rectangle area corresponds to an overview pattern.	54
5.11	Representation of the questions answered over time. This user is an example of skip behaviour.	55
5.12	Velocity in time.	55
5.13	Representation of the difference of results when applied the zapping correction. These show the signal of velocity over time in seconds, the change of question is noted by the change of colour, between blue and light blue, and at the beginning of the new question it is the number of the item. The black vertical lines are the mouse click (one for mouse down and one for mouse up). With fast changes the number of items is aligned vertically.	56
5.14	Representation of <-turn pattern. In blue is presented the mouse movement and in red the mouse click.	58
5.15	Representation of the questions where the mouse is located over time. The red circles represent the mouse clicks. The rectangle area corresponds to a revisit behaviour.	58
5.16	Skin conductance response morphology and respective first and second derivatives and time parameters, from [92].	68
5.17	Example of EDA-based function and monetary loss function. The first plot presents in red the moments in which the subject loses money and in green the moments in which he wins, the lines' width are bigger for bigger losses (or wins). The second and third plots are the loss wave and the "Average of the total SCR signal" for the 1st block.	72

6.1	Details about what will be explained and what are the outputs of the Chapter "Modelling personality using machine learning" in the context of this thesis.	74
6.2	Steps in modelling of features in machine learning to identify the optimal subset of features that best predict the Big Five dimensions. Steps with * means it is run several times according to parameters variation.	75
6.3	Violin plots of each personality scale distribution in Study 2 and 3.	81
6.4	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 2 and 3 based on mouse movements features in online survey.	85
6.5	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 2 and 3 based on the IGT features. . .	91
6.6	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the mouse movements features in the IGT.	97
6.7	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the pupil features during the IGT.	99
6.8	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the Electrocardiogram (ECG) features during the IGT.	102
6.9	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the BVP features during the IGT.	105
6.10	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the EDA features during the IGT.	110
6.11	Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the biosignals features during the IGT.	114
7.1	Details about what will be explained and what are the outputs of the Chapter "Application in Medical Decision-making" in the context of this thesis. . . .	121
7.2	Violin plots of each personality scale distribution in Study 4.	122
7.3	Plot of the observed versus predict values of personalities and respective histogram of the absolute error for Study 4 based on the pointer movements features personality questionnaires.	124
A.1	Thesis structure with detailed outputs.	170
B.1	Mouse movements of a questionnaire from the person with the minimum and the person with the maximum percentage of uncertainty items.	177

LIST OF TABLES

2.1	ECG components and respective duration [42, 132].	11
2.2	EDA components and respective values [31, 42].	14
2.3	Personality dimensions main traits and adjectives that characterize low and high scores. Adapted from [177, 185].	23
3.1	State of the art in predicting personality based on biological responses to emotional videos. OCEAN represents the big-five traits - Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism. Evaluation values correspond to F1-scores.	28
4.1	Conditions and medications of the three hypothetical patient cases.	41
5.1	Validation file output from Study 1.	49
5.2	Details about features extracted in spatial domain. Distribution and range values from Study 1. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	51
5.3	Details about features extracted in temporal domain. Distribution and range values from Study 1. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	53
5.4	Details about features extracted by the identification of micro-behaviours. Distribution and range values from Study 2. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	59
5.5	Features extracted from the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	62
5.6	Contextual features extracted from the mouse movements in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	62

5.7	Features extracted from the pupil diameter signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT and \$ the phase of the trial (c=choice; a=anticipation; f=feedback)). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	63
5.8	Features extracted from the ECG signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	65
5.9	Features extracted from the BVP signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	68
5.10	Features extracted from the EDA signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT and \$ the phase of the trial (c=choice; a=anticipation; f=feedback)). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).	70
6.1	Final number of subjects to build models.	80
6.2	Personality results for Study 2 and 3.	82
6.3	Details about the best predictive model based on the mouse movements in online surveys for each personality scale in Study 2 and Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	84
6.4	Features with high importance for predicting openness with mouse features.	86
6.5	Features with high importance for predicting conscientiousness with mouse features.	88
6.6	Features with high importance for predicting extraversion with mouse features.	89
6.7	Features with high importance for predicting neuroticism with mouse features.	90
6.8	Details about the best predictive model based on the IGT features for each personality scale in Study 2 and Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	90
6.9	Features with high importance for predicting openness with IGT features.	92
6.10	Features with high importance for predicting extraversion with IGT features.	93
6.11	Features with high importance for predicting agreeableness with IGT features.	95
6.12	Features with high importance for predicting neuroticism with IGT features.	95
6.13	Details about the best predictive model based on the mouse movements features in the IGT for each personality scale in Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	96

6.14	Details about the best predictive model based on the pupil features during the IGT for each personality scale in Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	98
6.15	Features with high importance for predicting openness with pupil features. .	100
6.16	Features with high importance for predicting extraversion with pupil features.	101
6.17	Details about the best predictive model based on the ECG features during the IGT for each personality scale in Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	101
6.18	Features with high importance for predicting agreeableness with ECG features.	104
6.19	Details about the best predictive model based on the BVP features during the IGT for each personality scale in Study 3.	104
6.20	Features with high importance for predicting openness with BVP features. .	106
6.21	Features with high importance for predicting conscientiousness with BVP features.	107
6.22	Features with high importance for predicting agreeableness with BVP features.	108
6.23	Features with high importance for predicting neuroticism with BVP features.	109
6.24	Details about the best predictive model based on the EDA features during the IGT for each personality scale in Study 3.	109
6.25	Features with high importance for predicting openness with EDA features. .	111
6.26	Features with high importance for predicting conscientiousness with EDA features.	111
6.27	Features with high importance for predicting extraversion with EDA features.	112
6.28	Details about the best predictive model based on the biosignals features during the IGT for each personality scale in Study 3. <i>CC</i> are the features resulted from the feature selection based on the correlation coefficient and <i>GFS</i> are the features resulted from the greedy forward selection method.	113
6.29	Features with high importance for predicting openness with biosignals features.	116
6.30	Features with high importance for predicting extraversion with biosignals features.	117
6.31	Features with high importance for predicting agreeableness with biosignals features.	118
7.1	Personality results for Study 4.	122
7.2	Details about the application of openness and extraversion predictive models based on the pointer movements features in each case of MISI and personality questionnaire in Study 4.	123
B.1	Regression coefficients of the ten most relevant features.	175
B.2	Model performance evaluation measures.	176

ACRONYMS

AC	Alternating Current.
ADC	Analog-to-Digital Conversion.
ANS	Autonomous Nervous System.
ApEn	Approximate Entropy.
BPM	Beats per Minute.
BVP	Blood Volume Pulse.
CD	Correlation Dimension.
DC	Direct Current.
DDIs	Disease–Disease, Drug–Disease, and Drug–Drug Interactions.
DFA	Detrended Fluctuation Analysis.
ECG	Electrocardiogram.
EDA	Electrodermal Activity.
EEG	Electroencephalography.
EMG	Electromyography.
ER-SCRs	Event-Related Skin Conductance Responses.
ET	Extra Tree.
FD	Fractal Dimension.
fMRI	Functional Magnetic Resonance Imaging.
FN	False Negatives.
FP	False Positives.
GB	Gradient Boosting.
GSR	Galvanic Skin Response.

ACRONYMS

HCI	Human-Computer Interaction.
HE	Hurst Exponent.
HF	High Frequency.
HR	Heart Rate.
HRV	Heart Rate Variability.
IGT	IOWA Gambling Task.
LF	Low Frequency.
LLE	Largest Lyapunov Exponent.
MEG	Magnetoencephalography.
MISI	Multimorbidity Interaction Severity Index.
MLR	Multiple Linear Regression.
MSE	Mean Squared Error.
NS-SCRs	Non-Specific Skin Conductance Responses.
PGR	Psycho-Galvanic Reflex.
PPG	Photoplethysmogram.
PSD	Power Spectral Density.
RED	Remote Eyetracking Device.
RF	Random Forest.
SampEn	Sample Entropy.
SC	Skin Conductance.
SCL	Skin Conductance Level.
SCR	Skin Conductance Response.
SD	Standard Deviation.
SMI	SensorMotoric Instruments.
SNS	Sympathetic Nervous System.
SSF	Slope Sum Function.
SSR	Sympathetic Skin Response.
SVR	Support Vector Regression.
TINN	Triangular Interpolation of the NN Intervals.

TN True Negatives.

TP True Positives.

VLf Very Low Frequency.

MOTIVATION

1.1 Background

Clinical decision-making for patients with multiple acute or chronic diseases (i.e. multimorbidity) is complex [158, 259, 272]. The clinical guidelines for multimorbid patients are limited in number, even for more frequent cases of multimorbidity and, therefore, clinical decision-making for multimorbid patients relies on guidelines that were developed for the treatment of single diseases [109, 173, 256]. These guidelines are inadequate for multimorbid patients because they do not address the combined impact of potentially harmful drug–drug and drug–disease interactions or help the physician to determine a therapeutic path through multiple drug–drug and drug–disease interactions within a patient.

The complexities of decision making in this situation can mean that there is often no 'right' treatment, making it necessary to balance the trade-offs between the benefits and risks of different treatment strategies [84]. This highlights the point that every patient is unique and requires a personalized approach. These complexities are also quite demanding for less experienced clinical decision-makers when trying to develop a therapeutic strategy that safely manages potentially harmful drug–drug and drug–disease interactions and meets the particular needs of the patient [153, 240].

1.2 Relevance

Between 20–30% of the population (e.g., [158]), 55–98% of persons older than 65 years (e.g., [272]) and ca. 90% of hospitalized inpatients are multimorbid [256, 259]. There is an adverse impact of multimorbidity on health outcomes, quality of life, physical disability, and mortality [173]. The burden of multimorbidity is reflected in disproportionately

higher health care resource utilization and costs [109]. These increase exponentially with the increasing number of concomitant diseases, [109] and the number of concomitant diseases increases with age [84] (see Figure 1.1). Aging is a driver of multimorbidity prevalence [258] and the increasing rate of population aging is strong and expected to continue for years to come [66]. The impact of drug–drug and drug–disease interactions and polypharmacy [240] exceeds that attributable simply to the combined impact of individual diseases [32]. This is due to the cumulative effects of multiple drug–drug and drug–disease interactions within a patient, which intensifies the difficulties, resource use and costs of managing multimorbid patients [260].

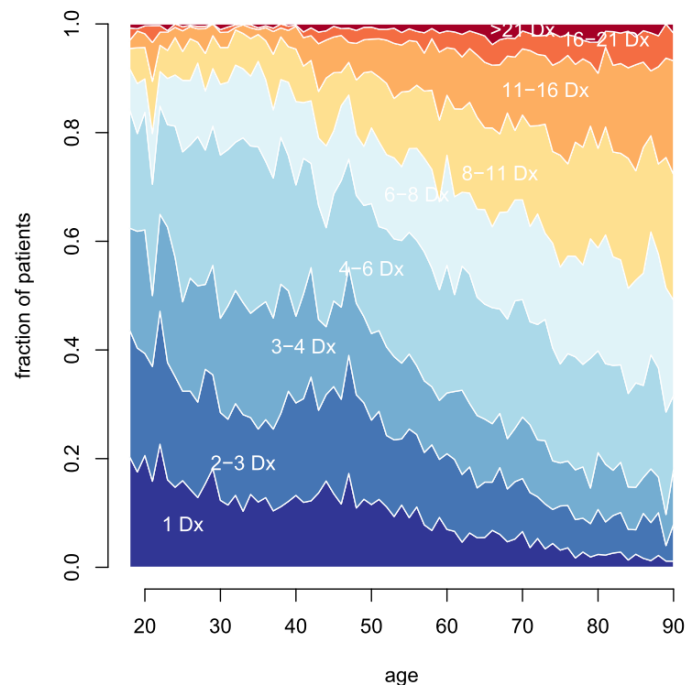


Figure 1.1: Distribution of diagnoses per inpatient in different age groups of a major city hospital. The in-hospital patient sample is predominantly multimorbid, with MM increasing with age (adapted from [71]).

Importantly, multimorbidity tends to form disease clusters (or disease combinations). For example, in relation to cardiovascular disease, coronary heart disease, cardiac insufficiency, stroke, hypertension, diabetes, dyslipidemia, kidney problems tend to co-occur [20]. However, a global perspective shows the emergence of new disease clusters that relate to different and changing demographics and epidemiological patterns of multimorbidity across different populations and countries [179]. For example, low-to-middle-income countries are experiencing a rapid emergence of new multimorbid disease patterns and trends in non-communicable diseases in addition to infectious communicable diseases [179]. The emergence of new combinations of co-occurring non-communicable diseases and infectious communicable diseases is increasing the complexities of clinical decision making and introducing risk in the management and healthcare of patients [148, 178]. A better understanding of how clinical decision-makers develop therapeutic

strategies to safely manage potential drug–drug and drug–disease interactions and meet patients’ needs on a personalized basis is needed.

1.3 The present research question

One aspect of decision making, such as when considering multiple Disease–Disease, Drug–Disease, and Drug–Drug Interactions (DDIs), may be reduced to first developing an understanding of individual decisions under conditions of risk and uncertainty. Making such decisions is a complex cognitive and affective process [63, 117]. Physiological signals have been used to highlight the role of affective processes in decision making [23, 112, 116, 166]. The decision process is reported to be strongly influenced by somatic markers, i.e., physiological signals that can convey the emotional value of choice options and influence the decision-making process [24, 63, 147]. Another aspect of decision making under conditions of risk and uncertainty is whether and how personality affects decision-making [21, 129, 205]. The close relationship between affect and personality (e.g. [175, 252]) led to the research question: What is the effect of personality in decision-making? [21, 129, 205].

This research project addresses the identification of personality traits in a decision-making process through human behaviour. A further connection with decision-making styles can train and guide less experienced clinical decision-makers based on experts with a similar personality. Accordingly, this thesis main objectives are:

1. Describe psychological and situational factors that influence real-world medical decision-making tasks. This integrates the preparation of decision-making tasks with acquisition of electrophysiological signals and Human-Computer Interaction (HCI) and development of processing tools;
2. Through machine learning algorithms, model the impact of these factors on individual decision-making processes;
3. Provide predictive indices of personality in medical decision-making.

Regarding the first goal, a variety of sources are explored to extract human behaviour from decision-making tasks. We collected data from HCI, particularly the pointer movements, from the decision-making task and physiological data, taking into consideration the role of affective processes in choice-making [23, 112, 116, 166]. These signals are processed to create a set of features that are descriptive of psychological and situational factors.

The second goal consisted of exploring data and define which data is informative to meet relevant conclusions. This is a standard procedure in data mining, in contrast to psychology that the majority of research is driven by theory. In this phase, different machine learning algorithms are used to combine the extracted information and establish

a relation with personality traits. From this approach, a set of predictive models are returned for each personality trait and data source, which evaluation metrics were adapted according to restrictions related to the studies carried out.

The last goal comprises a medical decision-making task in the context of multimorbidity, in which the predictive models previously built are applied and tested.

1.4 Thesis Structure

This thesis documents the work developed during a PhD program. It is organized by eight chapters and four appendices. Figure 1.2 presents the structure of this thesis, with the question to be resolved and respective objective in the main chapters. These are further described.

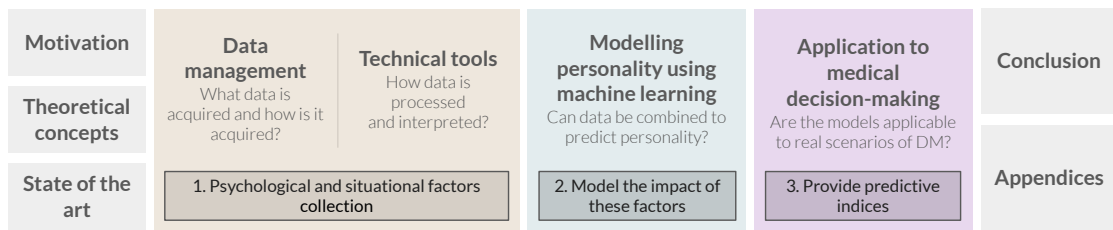


Figure 1.2: Thesis structure.

Chapter 1 introduces the background and relevance of this study to then present the research problem, including the main goals of this thesis. At last, the structure of the thesis is presented. Chapter 2 introduces the topics addressed throughout the present thesis. This covers an introduction to psychophysiological signals, human-computer interaction, decision-making tasks and personality. A literature review of the analysis of human behaviour, including personality, based on human-computer interaction, decision-making tasks, physiological signals and medical decision-making tasks are detailed in Chapter 3.

In Chapter 4, the data acquisition systems used and specific adaptations performed according to our context are presented. The scientific computation required to process the data acquired is also introduced. At last, the participants and procedure of the four studies carried out in this thesis are described in this chapter. The technical tools used to process and extract useful information from the data acquired during the different studies of this thesis are presented in Chapter 5. These features are then combined using machine learning algorithms, which are introduced in Chapter 6, to build predictive models of personality, which results are also described in the current chapter.

The produced models are finally applied to medical decision-making contexts and its results are presented in Chapter 7.

The last chapter, conclusions, includes a general discussion of the outcomes of the thesis, a reflection about the implications of this work and finalizes with applications and future work.

Four appendices are also provided. Appendix A presents a diagram with a detailed structure of the thesis, in which the outputs of each chapter are provided. This diagram is recalled in the document to help the reader to link the outputs of some chapters as the input of others. Appendix B explains the whole process to build the model of uncertainty. The Appendix C and D present some of the documentation given to the participants during the studies.

THEORETICAL CONCEPTS

To simplify the understanding of the work developed in this thesis, this chapter is an introduction of all the topics further addressed.

To interpret changes in physiological signals that are not caused by diseases, but by individual characteristics, it is firstly introduced the nervous system and how it can be sensed in the human body. Then, a brief description of physiological signals and how its acquisition is made is included, followed by the physiology analysis and signal structure of the biosignals used: Electrocardiogram (ECG), Electrodermal Activity (EDA) and Blood Volume Pulse (BVP).

Considering that human-computer interaction can also be a source of data on individual characteristics, a description of eye-tracking and pointer tracking systems is also included in this chapter. The eye-tracking system enables the acquisition of a different biosignal: the pupil diameter.

The process of decision-making in the context of this thesis is generally introduced and medical decision-making is then considered at greater depth.

A more detailed treatment of personality is provided as this is not typically addressed in the biomedical engineering field.

2.1 Physiological Signals

Physiological signals, or biosignals, are the record of an electrical, chemical or mechanical activity that occurs during a biological event that can be measured, analysed and processed [82].

The information collected from sensing technology in physiology is remarkably important to assess the human functional state, which may be useful for medical diagnosis.

Considering the uncountable physical phenomena, biosignals development and enhancement is a continuous process. For that reason, human health monitoring systems are increasingly used. However, the number of sensors in use compromises patient's comfort while using the system, thus it should be established an equilibrium between these factors [104].

Over the years, different methods for biosignals classification were used according to diverse characteristics of the signal, such as waveform shape, temporal properties and its origin. The last, and more complete approach is making the classification by its origin [82, 104]:

- Bioelectric: a measure of the electric field that is propagated by the cells (e.g. ECG);
- Biomagnetic: a measure of the magnetic fields (e.g. magnetoencephalogram);
- Biochemical: give information about the levels of chemical substances in the body (e.g. pressure of oxygen in the blood);
- Biomechanical: a measure of mechanical functions (e.g. mechanorespirogram);
- Bioacoustic: a measure of biological events that produce sounds (e.g. listening to the heart can help to diagnose heart valve's malfunctions);
- Biooptical: a measure of biological events with an external light-medium (e.g. measuring the fluorescence characteristics of the amniotic fluid to check fetus health).

To extract information from the biosignals, the raw data directly acquired by the sensor usually has some artefacts that need to be taken into account. When artefacts are caused by movements or environment noise, these could be reduced by improving the acquisition protocol, but when they are caused by individual differences or other biological events that could interfere with the desired signal, processing tools must be applied [76, 106].

Pre-processing tools are important to provide a more comprehensible result for the user and to facilitate the post-processing execution. The signal pre-processing removes endogenous effects, resulting from other biosignals interference, and exogenous effects, such as distortion and background noise [76].

The steps usually performed in signal acquisition and processing are sequentially presented in Figure 2.1. Firstly, the signal is detected by the sensors and the analogical signal is pre-processed with an amplifier and a filter to remove the undesirable part of the signal. This filter must have a constant modulus and a linear phase-frequency response to avoid relevant information losses. After that, the signal is converted from analogic to digital to certify its use by digital processors. For this, the signal is transformed into discrete values of amplitude and time. Although these processes imply loss of information, when the hardware is well designed, the inherent advantages are promising, facilitating the implementation of post-processing techniques. The digital processing varies according to

each biosignal and its final purpose. The most common strategies are filtering, averaging techniques and spectral estimators [76, 106].



Figure 2.1: Signal acquisition and processing steps. Based on [106].

In the following sections are introduced the nervous system and the biosignals acquired in this thesis: electrocardiogram (electric), electrodermal activity (electric) and blood volume pulse (optical).

2.1.1 Nervous System

The human body is composed of a set of physiological systems that work together to perform complex functions for the maintenance of the full-body homeostasis. The system responsible for coordinate the functions of all parts of the body is the nervous system [106].

Anatomically, the nervous system is subdivided between the central nervous system (brain and spinal cord) and the peripheral nervous system (cranial and spinal nerves). However, for this work, the division of the nervous system in terms of functionality has more relevance. This comprises [83, 106, 146]:

- Somatic nervous system: responsible for carrying and processing conscious and unconscious sensory information and the control of voluntary muscles (skeletal musculature);
- Autonomic nervous system: responsible for the transmission and processing of sensory information from visceral organs and for the control of involuntary muscles (cardiac and smooth muscles) and glands of the viscera. In other words, this system maintains homeostasis.

The physiological measurements involved in this work are more related to involuntary muscles or glands regulation and, consequently, to the autonomic nervous system. This system is divided into three categories: sympathetic, parasympathetic and enteric system. The sympathetic system acts in emergencies, to increase the activity of an organ or a gland. The parasympathetic system has the opposite effect, acting to conserve the body resources and to reach a relaxation state. The enteric is a system that could be independent of central nervous system control and is more related to gut functions [83, 146].

Although sympathetic and parasympathetic activates exactly the same body parts, they act in opposite ways. Sympathetic activation increases heart rates and blood pressure, stimulates the sweat glands and constricts pupil, in contrast to the parasympathetic

system. Besides the muscles are not controlled by the autonomic nervous system, some hormones are released by a sympathetic activation that increases the muscle tension. In cases of stress or trauma, in addition to all the hormones released, the sympathetic system accelerates the biological processes [83, 99, 104, 146].

2.1.2 Electrocardiogram

The heart is the organ responsible for receiving venous blood, eject it to pass through the lungs, receive the oxygenated blood and then pump it through the organs of the entire body. The coordinated contraction of heart muscles is controlled by electric current spread by specific heart cells. The coordination in each chamber pumping is obtained by the propagation of the electrical excitation along myocardia that produces the known structure of the ECG signal [104].

Although the first description of the recording of the body surface of electrical potentials generated by the heart was in 1887, it was only in 1924 that Willem Einthoven presented the mechanism of the electrocardiogram following the discovery of the string galvanometer [56]. Nowadays it is one of the most used diagnostic tools and, once the signal represents the electrical activity of the heart, ECG is a human vital signal.

To record ECG in a medical context, conventionally, electrodes are placed on each arm and leg, and six electrodes are placed at defined locations on the chest [139]. For research purposes, the number of leads can be reduced in accordance with its objectives.

The result of an ECG, as illustrated in Figure 2.2, presents a unique form with positive and negative waves. The waveform is obtained by the spread of the depolarization and re-polarization of the muscles and the signal of the waves depends on the spatial spread direction. The first wave is the P wave that represents the depolarization from the sinoatrial node to the atria, the QRS complex represents the total depolarization of both ventricles and the T wave the ventricles re-polarization. The atria re-polarization has a little amplitude and occurs at the same time as the depolarization of the ventricles, so it is not visible [42, 104].

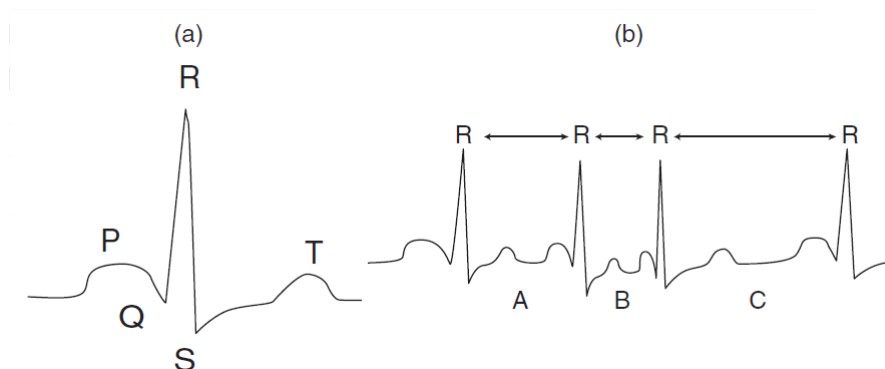


Figure 2.2: In (a) is represented a unique cycle of the ideal ECG and in (b) is represented four cycles with different R-R interval. From [99].

The typical time interval of the ECG waves are influenced by the autonomic nervous system and could be changed with health conditions. In Table 2.1 are the normal duration of each ECG component. The QT interval, which represents the action potential, is amended by Heart Rate Variability (HRV) [139].

Table 2.1: ECG components and respective duration [42, 132].

ECG Components	Description	Normal duration (ms)
P wave	Atrial depolarization	80-110
QRS complex	Ventricular depolarization	60-120
T wave	Ventricular repolarization	100
PR interval	Atrial depolarization plus atrioventricular node depolarization	120-200
QT interval	Action potential duration	200-500

The R peak is the most evident structure in the ECG (see Figure 2.2). Through its detection, it is possible to calculate the interval of time between two R peaks in milliseconds and extract the Heart Rate (HR) [104]. Moreover, the analysis of the HRV enables the extraction of linear (statistical, geometrical and frequency domain) and non-linear features that are proven psychophysiological measures. The Standard Deviation of the NN interval (beat to beat interval), the HRV triangular index and the Ratio between Low and High Frequencies (LF/HF), are frequently used in psychology research [3, 113, 155]. These tools have an important role associated with a high correlation between the HRV and Autonomous Nervous System (ANS) responses to regulate phenomena like sleep phases or emotional activity [104].

In healthy conditions the cardiac rhythm could be differentiated in 1) normal sinus rhythm (frequency between 60 and 100 Beats per Minute (BPM)); 2) sinus bradycardia (frequency below 60 BPM), that may result of increased vagal or parasympathetic tone; and 3) sinus tachycardia (frequency above 100 BPM), that may result of physiological response to physical exercise or psychological stress [156]. Directly related to heart function, ECG has been used in clinical applications to detect diseases like [167]:

- Cardiac arrhythmia: irregular heartbeat;
- Myocardial infarction: when blood flow decreases or stops to a part of the heart;
- Hypertension: high blood pressure.

In addition to heart-related diseases, ECG is also been used in diverse applications, such as biometrics or psychophysiological studies [50, 92].

2.1.3 Electrodermal activity

The skin is the major organ of the human body and provides sense and protective functions. On the one hand, the skin has receptors to provide sensory information related

to touch, pain or temperature. On the other hand, skin protects the entry of dangerous matter from the environment into the body. Besides, skin regulates the body temperature through the adjustment of the vessels volume or by the controlled production of sweat [31].

Besides the well-known functions of the skin, in 1888, Féré found that, while passing a small current across two electrodes on the skin, the electrical characteristics of the skin were influenced, i.e. skin becomes a better conductor of electricity when applied external stimuli. Later in 1889, Tarchanoff concluded that these electrical changes could also be measured without applying an external current [31, 42]. To support this electrical activity on skin, two theories were proposed: the vascular and the secretory theory. The first relates the increase of skin resistance with the increase of blood flow. The second defends that the skin resistance is caused by the activity of the sweat glands. Darrow (1927) confirmed the secretory theory by measuring the activity of the sweat glands and the skin electric activity, which were found to be closely related [65, 174].

There are two forms of sweat glands: apocrine and eccrine. The majority in the human body are eccrine glands, which have also been of primary interest to psychophysicologists. Their main function is thermoregulation, but when located at palmar and plantar sites the innervation of the glands is different from the rest of the body and they are more responsive to psychological stimuli than to thermal stimuli. Psychologists have measured psychological responses through sweat glands, which are directly related with sympathetic nervous activity, given that skin response is highly correlated with self-rated arousal [89, 143, 227, 263].

As represented in Figure 2.3, the eccrine gland has a long tubular portion, called duct, where the sweat will rise until reaching the sweat pore at the skin surface. The higher the sweat rises, the higher the skin conductivity and the lower the resistance measured at the skin surface. The amount of produced sweat and the number of glands activated is dependent on the sympathetic activation [42]. The measured signal at the skin surface was defined as EDA but different terminologies are also used: Skin Conductance Response (SCR), Sympathetic Skin Response (SSR), Galvanic Skin Response (GSR) or Psycho-Galvanic Reflex (PGR).

In line with how EDA was discovered, its acquisition is usually performed with two electrodes placed on the surface of the skin of the palms or fingers to measure the current flow and determine the skin conductance. In contrast to general biosignals, in which the gel of the used electrodes is hypertonic, for EDA this is not suitable because it has higher conductivity than the epidermis. To solve this issue, the NaCl-based electrolyte is appropriate to measure EDA, being a salt with monovalent ions in the epidermis surface and it is preponderant in sweat [31].

The acquisition of EDA results in a signal in microSiemens (μS) and an example of its structure is shown in Figure 2.4. In contrast to ECG, the EDA signal represents a slower physiological process, with a lower frequency, and it is not periodic. The signal is composed of tonic and phasic components. These are referred to as Skin Conductance

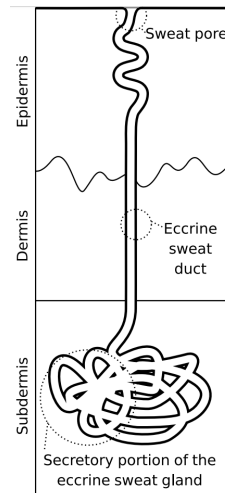


Figure 2.3: Diagram of eccrine sweat gland. From [92].

Level (SCL) and SCR, respectively. SCL is generally low during sleep and high in activated states such as rage or mental work. SCR can relate directly to stimulus presentation, as Event-Related Skin Conductance Responses (ER-SCRs), or occur as Non-Specific Skin Conductance Responses (NS-SCRs) without external stimulation. These responses are related to attention and are sensitive to stimulus novelty, intensity, and significance [220, 227].

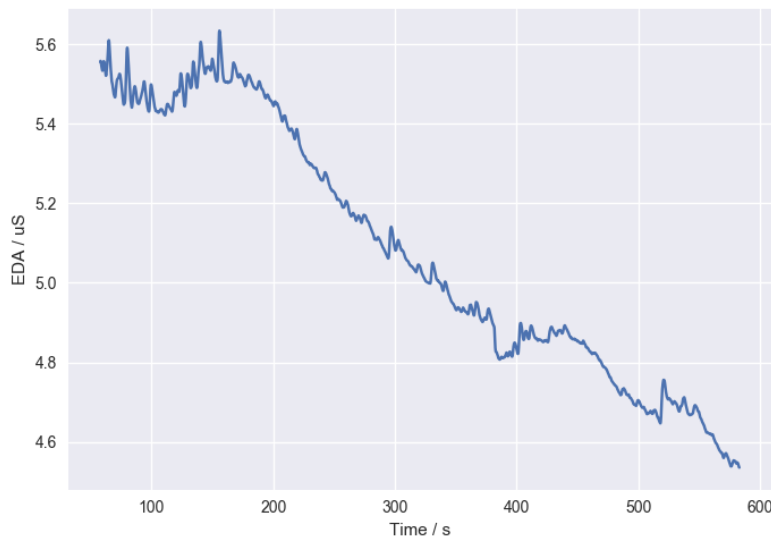


Figure 2.4: Example of an EDA signal.

The typical structure of a SCR associated with a specific stimulus is presented in Figure 2.5. Between the stimulus application (time t_0) and the signal response, emerges a latency time, without signal variance. Accordingly, as a result of the skin conductance increase, the signal rises and its local maximum amplitude represents the main parameter

in EDA analysis. It is evident that the recovery time is longer than the rising time [31, 42]. The typical time intervals of the last described EDA components are introduced in Table 2.2.

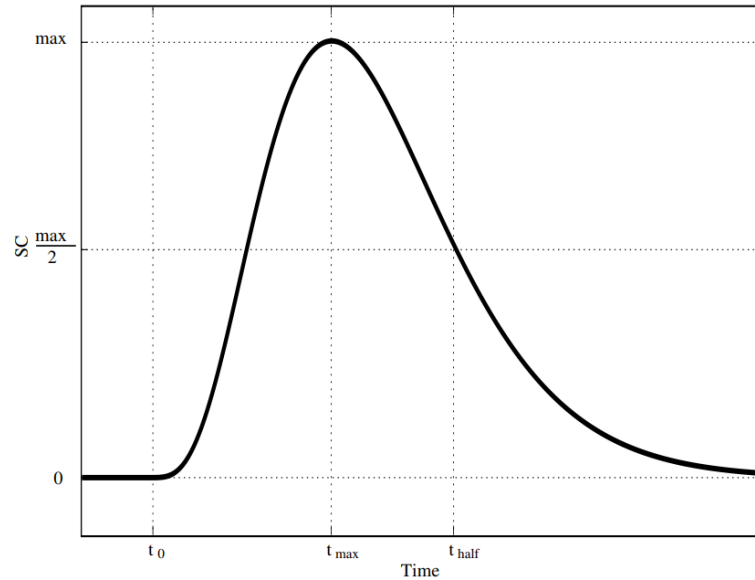


Figure 2.5: Illustration of a typical SCR. t_0 corresponds to the onset of the SCR, t_{max} the instant where the maximum value is reached and t_{half} the instant where the SCR returned to half of its maximum amplitude. From [92].

Table 2.2: EDA components and respective values [31, 42].

EDA Components	Description	Normal values
Change in SCL	Gradual changes in SCL measured at two or more points in time	1-3 μ S
SCL	Tonic level of the skin conductance	2-20 μ S ($f < 0.02$ Hz)
SCR	Skin conductance response	≈ 1 μ S ($f < 0.5$ Hz)
SCR amplitude	Local maximum in the SCR relatively to the SCR initiation	1 μ S
SCR latency	Time interval between stimulus and SCR initiation	1-3 s
SCR rise time	Time interval between SCR initiation and SCR peak	1-3 s
SCR half recovery time	Time interval between SCR peak and point of 50% recovery of SCR amplitude	2-10 s

2.1.4 Blood Volume Pulse

The increase of volume in arteries and capillaries caused by blood flow could be measured by a Photoplethysmogram (PPG) sensor that generate the BVP signal [134].

Alrick Hertzman described the PPG technique in 1937 for the first time, which waveform was defined as an amplified and high filtered measurement of light absorption by

the local tissue over time [6]. When infrared light is emitted at the surface of the skin, it is selectively transmitted, scattered, absorbed and reflected. In the case of infrared light, although there is light absorbed by the skin, part of the light is absorbed by the blood according to its volume. Measuring the quantity of light reflected back to the PPG detector, an average of blood volume in the arteries, capillaries, and any other tissue through which the light passed is possibly determined. Therefore, it is a simple-to-use and non-invasive technique [6, 7, 48, 134].

The acquisition is usually made placing the sensor on the ear lobe or finger, where the blood pulses are easily detected [7]. The electrical signal recorded from the PPG sensor, represented in Figure 2.6, comprises a Direct Current (DC) and an Alternating Current (AC) component. The DC component is steady and is related to the vascularisation of the tissue and skin colour, while the AC component is related to changing blood pulse volume. The AC component is modulated by the Sympathetic Nervous System (SNS) in frequencies ranging from 0.01 to 0.5 Hz. In the frequency range of 0.5-2 Hz, BVP is related to the mean heart rate. Given that the signal is a conversion of the light received by the detector into voltage, the signal is not a quantitative measurement [134].

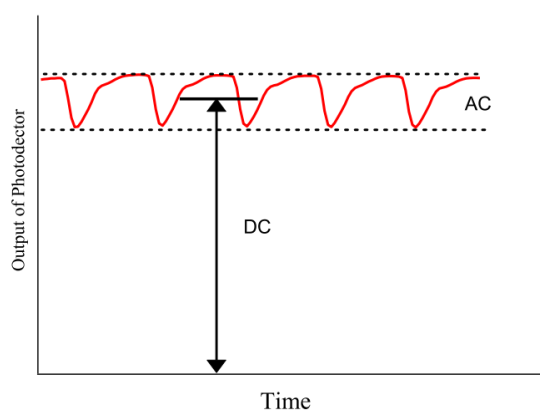


Figure 2.6: Illustration of a typical BVP wave, with AC and DC components identified. From [7].

The waveform pulse, presented in Figure 2.7, is the result of two phases: the anacrotic phase and the catacrotic phase. The anacrotic phase refers to the rising edge of the pulse, which is related to the systole, and the catacrotic phase refers to the diastole and wave reflections from the periphery. Also, a dicrotic notch usually appears in the catacrotic phase in patients with healthy compliant arteries. Heart rate can be simply estimated by the difference between two consecutive systolic peaks [7].

The primary application of BVP is to be used as ambulatory cardiac monitoring because it is easy to use, reduces the number of wires compared with ECG and is effective as a pulse counter and in detecting arrhythmia [29].

The amplitude of pulsation and blood flow are caused by an interaction between the cardiovascular, respiratory and autonomic systems, which extends the BVP applications to vascular assessment (e.g. detect arterial disease) and autonomic function (e.g.

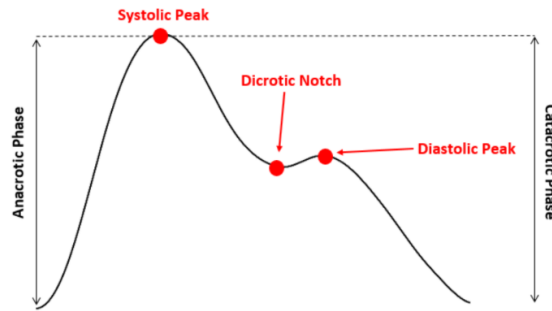


Figure 2.7: Illustration of a typical BVP pulse, with anacrotic and catacrotic phases identified.

thermoregulation). Changes in BVP amplitude provides information about sympathetic/parasympathetic and cognitive/emotional activation (i.e. SNS activation causes a decrease in amplitude) and, therefore, BVP measurements are commonly used as indications of psychological arousal in affective computing and Human-Computer Interaction (HCI). [7, 48, 134, 191].

2.2 Human-Computer Interaction

HCI is a multidisciplinary field of study that involves the design, implementation and evaluation of interactive systems, with special focus on the interaction between users and computers [74]. The influence of individually stable patterns of thinking, feeling and behaviour on HCI is of longstanding interest as it provides a means to study and improve HCI in terms of usability and user experience (e.g., [73, 200]). In psychology and cognitive science research, HCI is crucial to understand the user's perceptual, cognitive and problem-solving skills [74].

While a person is interacting with a computer, some information is received and other is sent. The user receives the information from the computer mainly through the senses, particularly vision, hearing and touch. The first information received by the user is by looking at graphical interface in the screen, becoming sight a fundamental sense. As an alert, computers sounds a "beep", and therefore, the output is given by hearing. Touch is more important as feedback of what the user is doing, by feeling the keys moving or the orientation of the mouse. The user sends information to the computer via motor control, mainly by typing or mouse control [74].

To analyse the interaction between the user and the computer, an eye tracker and pointer tracker were used in this thesis to examine human behaviour and infer personality. The following sections introduce eye tracker and pointer tracker.

2.2.1 Eye Tracker

The human eye is the organ able to capture, adjust and transform light from the outside world into the brain to be interpreted.

Briefly described (see Figure 2.8), when light approaches the eye, the first contact is with the cornea, a clear window at the front of the eye that covers the iris and the pupil. The cornea refracts the light that is then regulated by the iris, which contracts or expands to adjust the pupil size according to the intensity or availability of light. The focusing process is then done by the lens, which projects it onto the retina at the back of the eye. The retina works together with layers of cells to detect light and turn it into electrical impulses to be carried to the brain by the optic nerve processed by the brain. The sclera simply protects the eyeball [233, 279].

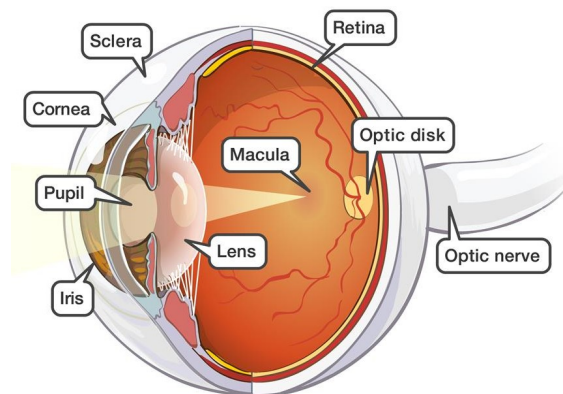


Figure 2.8: Eye anatomy. From [233].

In psychology experiments, the eye movements analysis has been used to monitor visual attention and provide insights into individuals' cognitive states. The instrument usually used to track eyes movements since the mid-1970s is the eye tracker [111, 207, 222].

To have more accurate acquisitions, eye-trackers systems detect eyes and head movements. More recent eye-trackers tracks the participants' eye-movements by tracking the positions of the participant's heads using eye-brows, noses, and lips. The corneal reflection from infrared lights and pupil centre detection are used to distinguish head and eye-movements [231]. Tobii and SensorMotoric Instruments (SMI) systems are examples of eye-trackers producers [235, 251].

The tracking of the pupil diameter by eye-tracker systems is also important to relate to the nervous system. As previously mentioned, the pupil works together with the iris to control the amount of light entering the eye. If the amount of light travelling through is excessive, the pupil constricts by the action of the sphincter muscle of the iris to reduce excessive light. In low-light environments, the pupil dilates to increase the amount of light entering the eye [28, 279]. Pupil dilation could also be a psychosensory reflex [64], caused by external sensory events (tactile, auditory, gustatory, olfactory, or noxious) and by psychological stimuli such as emotions or mental processes. This occurs because pupil diameter can be mediated by the autonomic nervous system: the dilator muscle is innervated by sympathetic nerves and its contraction causes pupil dilation; The sphincter muscle is innervated by parasympathetic nerves and its contraction causes

pupil constriction [33, 42, 64].

The human pupil size can vary from less than 1 mm to more than 9 mm [33]. In adults, pupils size are usually equal in size and the normal pupil diameter varies from 2 to 4 mm in bright light to 4 to 8 mm in the dark [238]. In Figure 2.9 is presented an example of the pupil diameter variation during a light stimulus. The time to react to a stimulus (latency time) can be 0.2 seconds and the peak occurs in 0.5 to 1-second [9, 85].

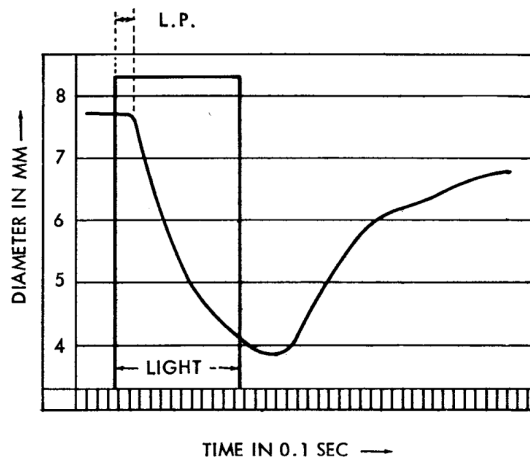


Figure 2.9: Example of a pupil reflex to light stimulus. L.P. is Latent Period. From [233].

2.2.2 Pointer Tracker

A pointer tracker consists of the collection of cursor positions by a software. The computer mouse first version was developed in 1964 by Douglas Engelbart, that used two wheels to slide across the desktop and transmit x and y coordinates to the computer. Nowadays, the mechanical mouse was replaced by an optical mouse, that incorporates a light-emitting diode on the base of the mouse. The fluctuations in the reflected intensity of the red light emitted are recorded by a sensor that translates them into relative x and y motion. The track-pad is an alternative to mouse in laptops, in which a specialized flat surface is capable of detecting finger contact and translate the motion to a relative position on the screen [74].

In comparison to eye-tracking, a wide range of eye movement behaviours have been associated with pointer movements behaviours. Data acquisition of cursor positions has the advantage of being easy to implement and is already integrated into the use of the computer. In contrast to eye-tracking that requires a specialized device and, consequently, requires the physical presence of the person to make an acquisition, the pointer acquisition can be done in any computer and, therefore, a great number of individuals can be simultaneously evaluated [52, 212].

In most cases, pointer data is used to test web pages usability in order to improve the user experience, but extraction of features from the pointer coordinates to study users' behaviour is increasingly being explored [54, 92, 114, 123, 127, 137].

To analyse mouse trajectories, a wide variety of measures in the temporal and spatial domain can be extracted. The most common temporal features are velocity and acceleration. Examples of spatial variables include distance travelled, angle of direction, curvature and straightness - the ratio between the Euclidean distance from the starting to the ending points and the total path distance [4, 53, 91, 203].

2.3 Decision Making

Almost everything a human does during his daily life involves decisions. This occurs when there is more than one alternative to choose and these led to different outcomes. Balleine defined decision making as "the ability of humans and other animals to choose between competing courses of action based on their relative value of consequences" [18].

While some decisions are momentary, such as "Shall I bring the umbrella today?", most decisions take time and, therefore, to guide and improve the decision making process, some authors describe it as a step-by-step process [105, 108, 157, 193]. For example, in 2008, Guo created a model to aid health-care managers [108]. This is called DECIDE, which consists of the following parts:

1. Define the problem
2. Establish the criteria
3. Consider all the alternatives
4. Identify the best alternative
5. Develop and implement a plan of action
6. Evaluate and monitor the solution

Taking into consideration the degree of uncertainty, there is a distinction between decisions under uncertainty and decisions under risk. A situation where the outcomes are known but not their probabilities refer to uncertainty. Risk is when in a situation the decision-maker knows with certainty the probabilities of possible outcomes of choice alternatives [264]. To evaluate the decision-making ability, several gambling tasks were developed. Most of them, like the IOWA Gambling Task (IGT) [22] or the Cambridge Gambling Task [214], were used to simulate decision-making with a degree of uncertainty or risk.

Making a decision depends on many factors. It is a complex cognitive and affective process, so the outcome depends on the neurophysiological state of the decision-maker and could be affected by some kinds of brain damage or functional brain disturbances [34, 63, 117]. Factors, such as the past experiences, possible future gains [133], age and individual differences [67] also influence the decision-making process.

2.3.1 Medical Decision Making

Every day physicians confront complex cases with many variables to handle. To understand and guide the medical decision-making process, systematic approaches to describe clinical thinking were conducted. As an example, Weed proposed problem-oriented thinking and recording that comprises the following steps [265]:

1. Create a database with complete history, physical exam and laboratory data;
2. Construct a list of inactive and active problems;
3. Define initial plans of treatment;
4. Register daily progress;
5. Record final progress note or discharge summary.

The decision-making process requires medical knowledge, a problem-solving strategy, a decision considering different probabilities for the possible outcomes and a risk-benefit balance.

2.4 Personality

Since the beginning of human interactions that people attempt to distinguish and, at the same time, aggregate individuals in terms of what they feel, think and act, to anticipate behaviours in particular situations.

Although the history of personality is relatively recent, it has not had constant importance or continue growing over time. James McKeen Cattell is considered the father of assessment psychology given that, in 1883, he pioneered the study of measuring individual differences with psychological tests. However, it was only during World War II that personality gained emergency as a discrete field in psychology, taking into account the needs for psychology services to the military during and after the war. It was during the 1930s and 1940s that Henry Murray introduced a set of psychological tests and behavioural measures to make a military selection for secret missions. The personality theories described in the books of Murray, Stagner and Gordon Allport were responsible for creating literature, studies programmes and research programmes in the context of personality [177, 267].

However, between the 1960s and 1980s, behavioural and humanistic perspectives considered the way personality was assessed irrelevant and improper. Furthermore, the assessment was also found as financially uneconomical. After this period, with the attenuation of radical behaviourists, researchers found individual differences consistent and many personal characteristics stable over time. With this, theories of personality have gained value and applied in many diverse fields such as health care, forensic or education [267].

Throughout the history of personality, theorists were influenced by different perspectives and their own life experience to construct their theories and, consequently creating distinct definitions for personality.

Biological theories believe that personality is influenced by genetics, and, therefore, studies include twins to relate traits with genetics. Theorists also investigate the impact of specific brain regions in personality function [47, 57].

Behavioural theories, in consistency with personality history, dominated during the mid-20th century. Behavioural theorists, such as Burrhus Skinner or John Watson, defend that personality is a result of the interaction between the individual and the environment and, therefore, conclusions are just accepted if based on observable and measurable behaviours. Bandura and Mischel considered that personality is the human capacity to influence their experiences and developments [47, 86, 216, 267].

Sigmund Freud presented a psychodynamic perspective, stating that personality is determined by the unconscious mind and childhood experiences, rather than modelled by present goals [47, 86, 216, 267].

The humanist theory focuses on the importance of individual experience, considering personality influenced by how people experience themselves and the world around them [47, 216].

The most prominent theory is the trait perspective, which describes personality as a set of traits, a trait being a stable characteristic that causes an individual to behave in certain ways or have certain emotional experiences. Allport was one of the first theorists presenting three traits: cardinals are the dominants traits and shape the individual behaviour; central traits are important but do not control all the time the person's behaviour; and secondary traits, that only expresses characteristics like preferences. With this view, Allport's definition of personality is "the dynamic organization within the individual of those psychophysical systems that determine his unique adjustments to the environment" [8, p. 48]. In 1949, Raymond Cattell distinguished source traits and surface traits according to how easy it is to identify the trait just by looking at the person's behaviour. Using 16 source traits, three categories of traits were created: ability, temperament and dynamic traits, with which Cattell created a questionnaire. Around the same time, Hans Eysenck based on biological factors described three dimensions of personality: extraversion-introversion, neuroticism-stability and psychoticism-normality. The theory of Eysenck captures individual differences identified in ancient times that were repudiated. The Greek physicians Hippocrates (around 400 B.C.) and Galen (around 200 A.D.) proposed the existence of four temperaments: melancholic, phlegmatic, choleric, and sanguine [47, 86, 216, 267].

An emerging consensus among theorists occurred during the last years of the 20th century, defending five factors in human personality based essentially in the biological basis of traits. The five-factor model, proposed by McCrae and Costa is detailed described in 2.4.1 since these five traits will represent personality throughout the development of this thesis [86].

Nowadays, the aim of the theorists is not to construct new theories about personality, but test hypothesis using the current theories to validate, extend and improve them, turning them more scientifically useful [216].

Different approaches can be used to identify and assess personal characteristics. Observing the person's behaviour or making a diagnostic interview to analyse the information about a person's attitudes and reactions are two strategies that could be very related to the situation in which the person is subject. These two approaches are also highly subjective and difficult to generalize. Two different options to gather information about the person from historical records or reports from other people who are close to the person or conduct self and peer assessments instruments to evaluating personality [267].

Identifying and evaluating the individuals' personality reveal details, such as individuals' weaknesses and strengths, preferences, needs or concerns. Assess personal characteristics is relevant in contexts like clinical, health care, forensic, educational and organizational environments [267].

2.4.1 Five Factor Personality

The Five Factor Personality, or Big Five, was, as mentioned before, a theoretical model proposed by McCrae and Costa, which is not a theory of personality but follows the basic principles of traits theory. The five factors model includes the following personality traits: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Traits are defined as "dimensions of individual differences in tendencies to show consistent patterns of thoughts, feelings and actions" [162]. What distinguishes these factors from the presented by Cattell or Allport is the evidence of temporal stability, so it should be stable across long periods of time, and the cross-observer validity, so it should be assessed similarly by different observers [47, 58].

Each trait is evaluated by a scale and, according to the tendency of the individual to behave in line with a high or low score of a personality dimension, the individual is characterized by the adjectives that describe the respective score. Some adjectives are identified in Table 2.3.

Neuroticism contrasts emotional stability versus individuals prone to psychological distress, unrealistic ideas, excessive craving or urges and maladaptive coping responses. Openness to experience is related to the breadth and depth of an individual's mental and experiential life, reflecting the appreciation of new experiences and exploration of the unfamiliar. Conscientiousness assesses the individual's degree of organization, persistence and motivation in a task- and goal-directed behaviour. Extraversion and Agreeableness are both related to interpersonal relations. Extraversion assesses quantity and intensity of interpersonal interaction while agreeableness assesses its quality [47, 162].

The first published inventory, the NEO Personality Inventory consisted of 180 items,

with six facet scales for just three domains: Neuroticism (N), Extraversion (E), and Openness to Experience (O). Later, NEO Personality Inventory-Revised (NEO-PI-R) has been developed with new facet scales for Agreeableness (A) and Conscientiousness (C), and replacement of 10 of the original N, E, and O items. In total, 240 items assess 30 specific traits within the Big Five traits [58]. The NEO Five-Factor Inventory (NEO-FFI) is a short-version with 60 items to assess only the five factors [163]. In all inventories, responses use a five-point Likert scale, from strongly disagree to strongly agree [57].

Dimension	Traits	High Scores	Low Scores
Openness	Fantasy	Curious	Conventional
	Aesthetics	Intellectual	Shallow
	Feelings	Imaginative	Simple
	Actions	Creative	Closed-minded
	Ideas	Flexible	Unartistic
	Intellect	Original	Unanalytical
Conscientiousness	Competence	Responsible	Aimless
	Order	Neat	Lazy
	Dutifulness	Organized	Irresponsible
	Achievement Striving	Ambitious	Careless
	Self-discipline	Achievement-oriented	Sloppy
	Deliberation	Efficient	Weak-willed
Extraversion	Warmth	Talkative	Introverted
	Activity	Sociable	Quiet
	Gregariousness	Warm	Reserved
	Assertiveness	Enthusiastic	Shy
	Excitement Seeking	Energetic	Silent
	Positive Emotions	Optimistic	Unadventurous
Agreeableness	Trust	Helpful	Hostile
	Straight-forwardness	Caring	Uncooperative
	Altruism	Nurturing	Rude
	Modesty	Cooperative	Jealous
	Tender-Mindedness	Trusting	Spiteful
	Compliance	Forgiving	Selfish
Neuroticism	Anxiety	Irrational	Calm
	Hostility	Nervous	Self-confident
	Depression	Inadequate	Even-tempered
	Self-Consciousness	Hypochondriacal	Hardy
	Impulsiveness	Pessimistic	Stable
	Vulnerability	Insecure	Unemotional

Table 2.3: Personality dimensions main traits and adjectives that characterize low and high scores. Adapted from [177, 185].

STATE OF THE ART

In this chapter, previous studies conducted to recognize individual characteristics based on human behaviour are explored. Human behaviour is analysed by the response of physiological signals, human-computer interaction, decision-making tasks and, lastly, clinical decision-making task. Although some studies used machine learning techniques to predict personality from human behaviour, for the best of our knowledge, there is a lack of studies investigating personality in medical decision-making contexts, particularly in multimorbidity.

3.1 Human behaviour analysis from physiological signals

The relationship between physiological signals and psychological factors have been investigated through the collection of several signals. Some authors examined the isolated signal of Electrocardiogram (ECG), Electrodermal Activity (EDA), Blood Volume Pulse (BVP), pupil and Electroencephalography (EEG) in association with decision-making tasks and psychophysiology, while others explore the combination of multiple signals including also respiration, Electromyography (EMG), Functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG), skin temperature and facial expressions.

According to the goals of this thesis, the literature review is more focused on studies that make an individual or associative analysis of pupil, ECG, BVP and EDA signals to predict personality, or emotions that could be associated to personality traits.

Although never related to personality, pupil diameter has been associated as a marker in decision-making tasks. The first study in this context observed, in cases of uncertainty and negative feedback, an associated bigger pupil diameter [219]. Using a different decision-making task, less uncertainty, independently of the outcome, results in

high variability of the pupil dilatation [202]. More recently, Lavín and his colleagues [145] measured the pupil diameter in the IOWA Gambling Task (IGT) and found only significant differences in pupil diameter in the second half of the game (trials 51-100), concluding that pupil is not only a marker of uncertainty but also of learned uncertainty. An increase in the pupil diameter is verified after positive and negative outcomes.

Several studies have explored changes in physiological signals from the autonomic nervous system and associate them to psychological states or emotions. De Pascalis et al. [68] identified deceleration in Heart Rate (HR) for high-anxiety subjects, after negative feedback in an emotional-word recognition task. While observing movies that elicit different kinds of emotions, frustration was related to EDA increases. The HR increases as a consequence of fear and decreases when the participant is angry [152].

Studies also show that machine-learning approaches can effectively recognize emotions based on multimodal physiological signals. Kim et al. [138] achieved good results for emotion recognition caused by music, using extended linear discriminant analysis. It was also found a positive correlation between EDA and EMG features and arousal change. Valence differentiation is found to be more related to ECG and respiration features. In [248] the acquisition and combination of BVP, EDA, respiration and skin temperature by a Gaussian kernel applied to support vector machines attain an average recognition of 56% for positive and negative emotions. Including EMG in the peripheral set of signals, the study of Koelstra et al. [140] classified arousal, valence and liking with an accuracy higher than 50% based on emotional videos. Even so, EEG and multimedia content analysis were also used as predictors and scored best for arousal and liking, respectively. Soleymani and his colleagues [237] attained the worst results for emotion recognition using peripheral physiological features (ECG, EDA, respiration and skin temperature) due to a high variance between participants. They used eye gaze data to extract pupil diameter and eye blinking features, that performed better for recognizing emotions. Furthermore, the rate of eye blinking was correlated with anxiety.

There are also plenty of research studies that investigate physiological responses in decision-making tasks, especially based on the IGT. With the objective of monitoring learning using physiological measures in a cognitive task associated to workload, decreasing effort over time was associated with a decrease in HR, an increased high-frequency Heart Rate Variability (HRV), pupil size decreased, and blink duration increased [39].

Studer et al. [242] monitored ECG and EDA during decision-making under risk and relate that with higher trait sensitivity to punishment (BIS) and lower trait sensitivity to reward (BAS). They found that when the chances of winning are high, HR increases for high BIS scores and low BAS scores.

In 2004, Crone et al. [62] conclude that good performers in the IGT reported an anticipatory slower HR and higher Skin Conductance Level (SCL) preceding disadvantageous decks. Following penalties, HR slowed and SCL increased for all performance groups. Following a similar approach, Goudriann et al. [102] compared the HR and Skin Conductance Response (SCR) of pathological gamblers and normal group. While the pathological

group showed a decrease in HR after disadvantageous and advantageous decks, normal subjects showed a decrease in HR after losses, but an increase in HR after wins. Also, normal participants presented higher anticipatory SCR when choosing "bad" decks.

Other authors supported the existence of higher anticipatory SCR previous to "bad" decks selection [116, 131, 246, 253]. Although good performance was associated to anticipatory SCR [44, 181], Suzuki et al. [246] found a clearly relation between the SCR in feedback phases and good performance in the IGT. Dunn et al. [78] declared that anticipatory SCR is achieved through experience, being developed over the game, with larger results for "bad" decks than for "good" decks, which is in accordance with previous studies [24]. This could mean that the anticipatory SCR is a consequence of conscious knowledge of the situation rather than being caused by just the decision-making process. In contrast to these finding, Tomb et al. [253] found no differences in anticipatory SCR throughout the game, which was later supported by the study of [107]. Guillaume et al. [107] also declared that performance in the IGT was correlated not with anticipatory SCR before advantageous or disadvantageous decks, but with the autonomic response, i.e. the difference between anticipatory SCR before advantageous and disadvantageous decks.

Werner and his colleagues [271] reported larger anticipatory SCR and HR to individuals with higher trait-anxiety, which proved to be a good predictor for IGT performance by regression analysis. Nevertheless, despite the study of Thompson et al. [250] confirms that anxiety and sympathetic responses to losses are strong predictors for IGT performance, they could not distinguish subjects with and without anxiety based on physiological measurements.

A recent study also found that IGT performance is poorer when stress is induced, which also results in increased blood pressure [234].

The first time personality was measured by physiological signals was in 1991 by Gilbert [98] in two different tasks: Venipuncture and speech. Venipuncture was used as a passive task, in which heart rate increases are related to higher neuroticism and low extraversion. The active task, during the speech, changes of HR had the opposite result: is higher for extraverted individuals and low neurotics. Skin Conductance (SC) was also measured but no correlations were found between SC changes and personality. In addition to HR and SC, facial expression and nonverbal behaviour were also evaluated.

In 2010, many biological measurements were explored in different situations, e.g. after the induction of anger, fear or anxiety, to be associated with personality [241]. Using multiple linear regression, the big-five personalities, except for openness, had a $r > |0.20|$ and at least 95% confidence interval ($[|0.03|, |0.37|]$), being predicted by:

- Conscientiousness: high respiratory rate and short P-Q wave time;
- Extraversion: decrease of HR, increase of HRV and increased EMG activity;
- Agreeableness: high diastolic blood pressure and decrease of pulse wave velocity;
- Neuroticism: decrease of HR, reduction of p-wave amplitude, reduction of mean blood pressure and increase respiratory sinus arrhythmia.

The influence of personality dimensions in concealing guilt, were associated with biosignals. Larger SCR and stronger pulses in BVP were linked to low extraverted individuals. Stronger pulses were also observed in high openness subjects [283].

Many authors analysed the responses to emotional videos to predict personality, which results are reported in Table 3.1. All the studies have split the scales to have a classification problem, instead of regression problem, to build the predictive models, to after evaluating the results using F1-score, which best value is 1 [274]. Using linear support-vector machines, agreeableness and conscientiousness are best predicted by ECG and openness is best predicted by EDA [261]. Exactly with the same algorithm but with opposite results, openness and extraversion are better predicted by ECG and agreeableness, conscientiousness and neuroticism are better predicted by EDA [168]. More recently, using non-linear kernels (naive Bayes and RBF-SVM) ECG features had better results for agreeableness, conscientiousness and neuroticism, while EDA features were more accurate to predict openness [243]. Abadi et al. [2] combined features from ECG and EDA and with linear regression achieved the best predictive model for extraversion.

Table 3.1: State of the art in predicting personality based on biological responses to emotional videos. OCEAN represents the big-five traits - Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism. Evaluation values correspond to F1-scores.

Study	Model	Signal	O	C	E	A	N
Wache et al. [261]	Linear SVM	ECG	0.54	0.31	0.43	0.37	0.50
		EDA	0.91	0.28	0.14	0.34	0.20
Abadi et al. [2]	MLR	ECG+EDA	0.53	0.53	0.70	0.51	0.58
Miranda-Correa et al. [168]	MLR	ECG	0.65	0.45	0.49	0.57	0.18
		EDA	0.38	0.54	0.37	0.84	0.62
Subramanian et al. [243]	non-linear	ECG	0.49	0.60	0.56	0.55	0.58
		EDA	0.53	0.57	0.45	0.39	0.73

A study that related personality traits with HRV, found a high negative correlation between neuroticism and Power in High Frequency (HF) and a high positive correlation with Low Frequency (LF)/HF. A negative correlation between HF and openness reported [232].

Carter et al. [44] were the only ones exploring physiological responses in the IGT and its relation to personality, founding just a correlation between neuroticism and anticipatory SCR responses to reward.

3.2 Human behaviour analysis from human-computer interaction

From the moment in which the internet became indispensable in our daily lives through a computer, mobile devices or even smart watches, tons of personal data is continuously

injected. While the user interacts with the computer, individual characteristics and interests are manifested. Consequently, the analysis of human behaviour may infer user preferences and intentions, which are the key to improve online services and build personalized environments. Fields of research in psychology, cognitive neuroscience, marketing research and usability testing have a particular interest in this behavioural analysis. Understanding user behaviour in the context of making decisions, a complex cognitive and affective process [63, 117], has increasingly attracted attention in Human-Computer Interaction (HCI) research [75, 187].

To relate personality with computer interaction data, there are different sources of digital behaviours. Directly from the inputs given to the computer, the intentions of the users are identified and parameters from, for example, speech, writing of facial expressions can be used to recognize emotions or personality traits [17, 154]. From another point of view, a long-term analysis of specific choices that are made can also give insights about the user. Examples of studies in this regard associate to personality dimensions music preferences [210] or desktop structure [161]. The latter study concluded that conscientiousness predicts file organization on desktops and that neurotics may keep more desktop files.

Since the emergence of public profiles in social networks, like Facebook and Twitter, research to infer personality based on data published by the users themselves has been growing [16, 100, 142, 149, 159, 170, 180, 201, 204, 254, 262, 266, 278]. These studies used machine learning algorithms to predict Big Five personalities using data from Facebook or Twitter profiles, measures of social networks (such the number of friends), language used in social media, preferred music, or the content of a person's website. Although the first studies had better predictive results for some scales, after some improvements all the five factors start to be well predicted. Golbeck et al. [100] and Quercia et al. [204] attained the best result for openness. Despite extraversion and neuroticism were the worst results achieved by Quercia et al. [204], for Bachrach et al. [16] these were the best predictive models. Since 2013, all scales of personality were predicted with an accuracy higher than 60% [180, 201] and, in 2017, Li et al. [149] simply using multi-linear regression achieved mean absolute errors between 0.14 (for openness) and 0.18 (for extraversion). Despite the good results obtained, many online users are concern about privacy issues of this approach [51].

An alternative source of behavioural data that does not consider personal information and details is using the pointer tracking data. Previous studies regarding mouse tracking analysis are largely related to web pages usability testing to improve the user experience [13, 14, 54, 123, 127], especially after Fitt's law. Fitt's law [87] quantifies the pointing behaviour and, by measuring the time that is needed to use an interface, its efficiency is calculated. Some recent studies start to relate the user experience with psychology and affective computing. Arapakis et al. [11] used machine learning to predict user engagement using temporal, spatial and related to the target mouse features. Katerina et al. [136] extracted 30 mouse patterns and found a relationship between these patterns (e.g.

random movements or hovers) and perceived ease use, perceived usefulness, self-efficacy, willingness to learn or risk-perception.

One field of research of mouse movements is for user authentication. Revett et al. [211] and Gamboa et al. [92] build the profile of the user just based on mouse dynamics, demonstrating its efficiency in the authentication.

Concerning cognitive neuroscience, Pimenta et al. [195] found that a decrease in the cognitive skills is evidenced by a reduction of mouse acceleration and velocity. Seelye et al. [225] used just mouse movement variables to distinguish older adults with and without mild cognitive impairment. Some authors also found a relation between pointer movements to emotions [114, 276, 280]. Hibbeln et al. [114] concluded that negative emotion can be inferred with an accuracy of 81.7% based on the mouse distance, that increases, and on the speed of the mouse cursor, that decreases.

Literature also supports that personality can be expressed based on computer interaction. Brebner et al. [35] observed extroverts to exhibit higher levels of motor activity with their clicking buttons with a higher frequency when it caused a change in visual stimulation. Concerning personality and interactive behaviours, Saati et al. [217] found that extroverts tended to interact faster with the user interface than introverts, and replicates Doucet and colleagues [77] observations of correlations between extroversion and the speed of human movement. More recently, Khan et al. [137] recorded keys pressed and mouse clicks and found a correlation between them and some main traits and sub traits of personality. Using linear regression, Khan et al. have predictive models of the big five traits with a root mean squared error between 0.27 and 0.29.

3.3 Human behaviour analysis from decision-making tasks

The evaluation of decision-making is widely made by the IGT [22], a game with four decks, in which the player wins or loose money in each trial and the goal is to win as much money as possible. There are two decks more advantageous (deck 2 and 4) than the others (deck 1 and 3). Previous studies [162] defended the theory that is during decision-making under ambiguity when the personality is more expressed.

In the IGT, individual variability in decision-making performance relates to variability in personality traits (for a recent review, see [182]). These traits include impulsivity [61, 244], reward sensitivity, punishment sensitivity and sensation-seeking [192], negative emotions [208], and high behavioural activation (BAS) and low behavioural inhibition (BIS) [88, 119, 244]. De Vries et al. [69] conclude that, in an early stage of the IGT, positive mood is related to better performance. Buelow et al. [40] found a relation between the decks selected and personality characteristics. Individuals with negative mood, drive, impulsivity, and sensation seeking select more Deck 2 and less Deck 4.

Some authors also explore the relation between Big-five personalities and IGT. Neuroticism is negatively associated with IGT performance in adolescents, preferring good decks late in the task [120, 125]. The same conclusion also applies to older adults, in

which high neuroticism was associated with low performance in the IGT [70]. No previous study reported the same result for adults. Byrne et al. [41] concluded that Agreeableness trait negatively predict the IGT performance. The recent study of Yilmaz et al. [277] showed that individuals who are high in openness to experience exhibit relatively ineffective use of decision-making skills.

3.4 Human behaviour analysis from medical decision-making tasks

Personality has been widely related to job performance [190]. In the case of physicians, they tend to be high in conscientiousness, sensation seeking, resiliency, and empathy but low in extroversion, neuroticism, and agreeableness (for a review see [169]).

Pilarik and Sarmany-Schuller [194] evaluated personality factors related to emotions in a medical decision-making process. They concluded that the performance of the IGT is characterized by emotional stability, extraversion, and fast responses. They also found some gender difference, given that for men, low scores in neuroticism, high scores in extraversion and fast responses in Stroop test, which is a cognitive test, are predictors of best performance in decision-making. In the case of women, better decision-making is related to emotional intelligence (low emotional awareness and positive current conditions) and quick reactions in the Stroop test.

3.5 Conclusion

The literature addressed in this chapter confirms the increasing interest in identifying individual insights, such as emotion or personality, through human behaviour, as an alternative to the gold-standard self-reported questionnaires.

Through physiological signals, many authors related their response with psychology and decision-making tasks and some used machine learning algorithms to predict personality, especially using ECG and EDA. Using the interaction with computers, the majority of the studies explored the information provided and revealed in social networks to predict emotions and personality using machine learning methods. The dynamics of the pointer movements were also associated with authentication problems, related to cognitive skills or, more recently, used as predictor of personality. Personality was also related to the IGT performance, but previous studies did not attempt to predict personality based on the game. In terms of medical decision-making, although personality and the IGT were used in this context, we could not find any study that explored personality in a medical real-scenario.

DATA MANAGEMENT

In the course of this thesis, several data management systems were used and some of them required modifications according to our purpose. The first part of this chapter describes each data acquisition system and what information is contained in the generated files. The structure of these files are important to further understand how the processing tools are implemented (introduced in Chapter 5). The last part of this chapter presents the participants and procedures of the studies performed in this thesis. Diagram 4.1 presents the main purpose of this chapter: to specify what data is acquired and how it is acquired. With the description of the data acquisition systems and studies performed during this thesis, is also possible to conclude which data is returned from each study. The integration of this chapter and its outputs in this thesis is represented in the diagram of Appendix A.

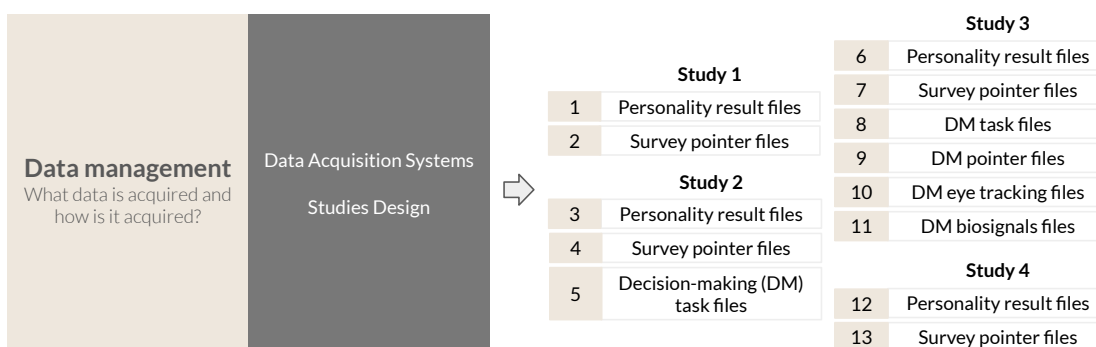


Figure 4.1: Purpose and outputs of the "Data Management" chapter in this thesis.

4.1 Data Acquisition

In this work, data is the decision-making tasks context data, eye-tracking data, physiological signals data, pointer data and questionnaires data and, therefore, it is collected

from several sources. The data was always recorded while a user was interacting with the computer. Below, are presented the two contexts in which different systems were combined to collect data. One is the decision experiment, that includes as acquisition systems the IOWA Gambling Task, eye-tracking and biosignals acquisition device. The other context is the online surveys, that, in addition to the questionnaires output, the pointer is also tracked.

4.1.1 Decision-Making Task

To run the experiment we used Presentation from Neurobehavioral Systems [247]. This software is a stimulus delivery and experiment control program widely used in behavioural, psychological and physiological experiments. An advantage of this system is the available communication with devices like fMRI or eye trackers. In addition to the quick and easy customization of parameters, the experiments could be completely programmed using two scripting languages: SDL and PCL.

These features allowed us to redesign the task (described in 4.1.1.1) and to connect and synchronize the stimulus PC, where the experiment is run, with the eye tracker workstation and the biosignals acquisition device. Figure 4.2 represents how the connections were made between systems. The biosignals acquisition device is simply connected with the stimulus PC via Bluetooth (detailed information in 4.1.1.3) and the Eye Tracker system includes a workstation that is connected with the stimulus PC via Ethernet and the Eye Tracker module, which is located under the stimulus PC, sends the data to the workstation via FireWire (detailed information in 4.1.1.2).

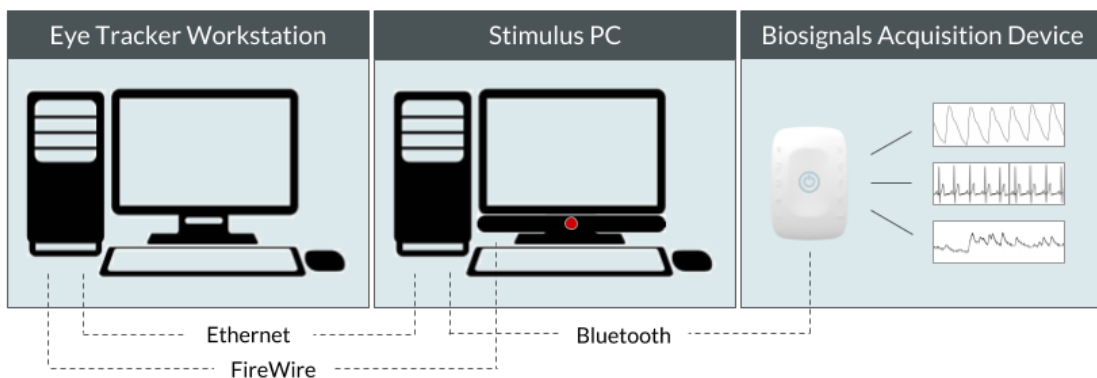


Figure 4.2: Experiment systems connection and synchronization.

4.1.1.1 Decision-making Task Simulation

The IOWA Gambling Task (IGT) was first presented by Bechara and colleagues in 1994 [22]. This task is a card game that simulates decision-making in an environment where the participant makes card selections one at a time. With the feedback, the participant should conclude that there is a strategy in this game, given that the card decks associated

with a high gain are associated with a high loss and the card decks with low gain are associated with a low loss, so the latter is more advantageous in the long run [12, 22].

The structure of the IGT was modified in terms of design and times configuration considering the simultaneous acquisition of pointer and eye movements.

To begin, an initial text informs the participants that the goal of the game is to maximize their winnings and that they are free to switch from any deck to another at any time. The participants began with a loan of 2000 CHF. No information is given about the distribution of probability and magnitude of gains and losses over the decks or how many trials there is to play. With some card selections, participants win money, but with other card selections, the wins are followed by monetary losses. More specifically, two of the decks provide large monetary gains, with a reward of +100, and even larger losses, with a probability of 1/2 to occur a penalty of -250 and with a probability of 1/10 to occur a penalty of -1250 (“bad” decks), while the other two decks lead to small gains, with a reward of +50, and even smaller losses, with a probability of 1/2 to occur a penalty of -50 and with a probability of 1/10 to occur a penalty of -250 (“good” decks). Strong performers learn to choose cards primarily from the “good” decks.

In Figure 4.3 is represented how the game was structured.

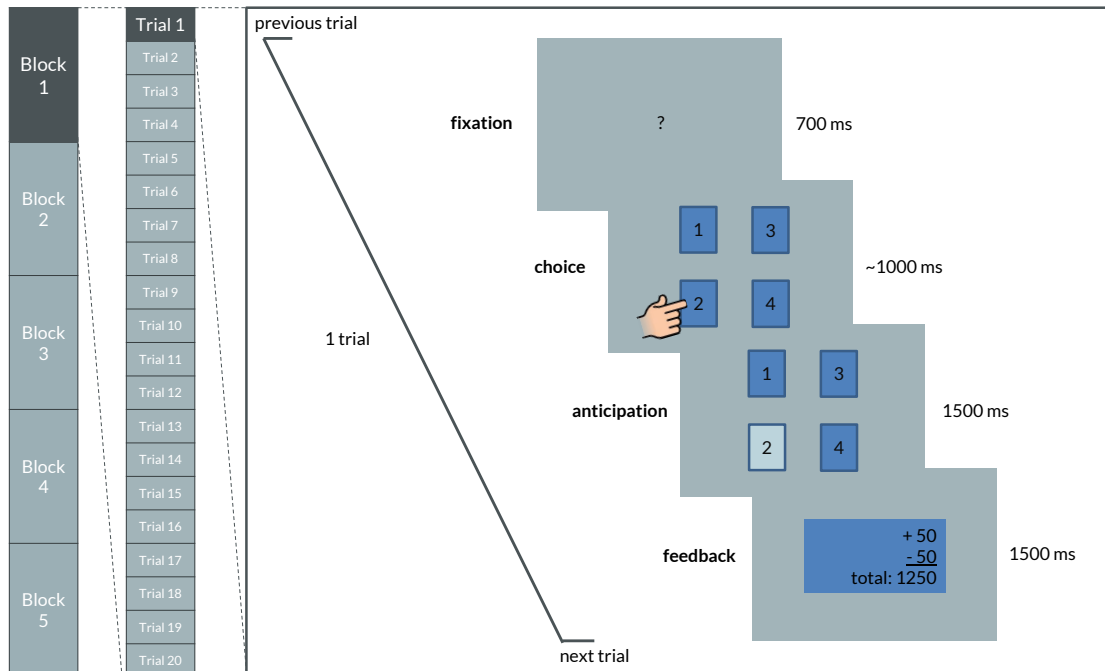


Figure 4.3: IGT schematic representation of the sequential phases of each trial and respective durations. The total game was divided into 5 different blocks, each one with 20 trials. A trial was composed by four phases, the fixation, the choice while the subject is deciding the deck he/she want to select, the anticipation phase to present the deck selected and, finally, the feedback with the monetary win, loss and the current money.

As is conventionally done, a learning profile during the IGT can be discerned from an examination of the card selections in blocks of 20 cards across the 100 card choices (block 1, cards 1–20; block 2, cards 21–40... block 5, cards 81–100). At the beginning of the task, a practice pre-test of two trials was applied to ensure that the participant understood the task.

In each trial, the participant is instructed to focus on the question mark. After a brief moment, a set of four cards is shown. The participant is told to choose a card from one of the decks by pressing the mouse button on the corresponding deck (choice phase). After choosing a card, a red rectangle appeared around the deck chosen and only after 1.5 seconds the win and punishment are shown as feedback. This delay was important to have an anticipation condition, as a cognitive stimulation for the participant. If the participant did not make a selection within 7 seconds, the choice phase was restarted.

The cards are usually horizontally distributed. We have decided to distribute them two on the top and two on the bottom to avoid eye-tracking and pointer moving around cards on the way to the desired cards.

Presentation automatically returns a data reporting file (logfile). The logfile contains information about the events and times of the scenario. In case of IGT, this file contains the following information:

```
1 Header (not printed on the file)
2 Scenario - Iowa Gambling Task
3 Logfile written - [Date and time]
4 Data (not printed on the file)
5 [Subject] [Trial] [Event Type] [Code] [event\_cond(str)] [trial\_number(num)
   ] [deck\_select(num)] [RT(num)] [reward(num)] [penalty(num)] [total(
   num)] [Time] [TTime][Uncertainty] [Duration] [Uncertainty] [ReqTime] [
   ReqDur] [Stim Type] [Pair Index]
6 More Data (no interest to us)
```

From this file, we were just interested in *Code*, that identifies the event as "fixed" or "feedback", in *deck_selected(num)*, *reward(num)*, *penalty(num)*, *total(num)*, *Time* and *RT(num)* which is the reaction time.

Taking advantage of the software tools available, the acquisition and recording of the pointer movements while doing the experiment was easily implemented. The generated PCL Output File [188] returned:

```
1 [Subject] [Trial] [Mouse Position X] [Mouse Position Y] [Date/Time]
```

All files generated (logfile and pointer file) include the subject name in the file name.

4.1.1.2 Eye-tracking

To acquire the eye movements we used SensorMotoric Instruments (SMI) systems [235]. This system provides behavioural and gaze analysis software for research in the fields of reading research, psychology, cognitive neuroscience, marketing research and usability

testing. From the available cameras, the one that fits gaze research on a computer monitor is camera Remote Eyetracking Device (RED). It is a non-invasive eye-tracking system with open communication interface via Ethernet and, with interest for us, is easily integrated with Presentation [235].

The system integrates an eye-tracking module with automatic eye and head tracker based on infrared eye cameras. Its main characteristics are:

- Sampling rate: 50/60 Hz
- Tracking resolution: $<0.1^\circ$ (typ.)
- Gaze position accuracy: $<0.5^\circ$ (typ.)
- Operating distance subject-camera: 60-80 cm
- Head tracking range: 40x20 cm at 70 cm distance
- Viewing angle: approx. $\pm 30^\circ$ hor./ 22.5° vert.

Despite that the software provides processing tools to the eye and head tracking data, we were just interested in the eye position data and in the eye pupil diameter over time.

SMI generates an iView Data File that is loaded into the IDF Converter to export the desired data. From this procedure, a text file is created and includes:

```
1 Header (not printed on the file)
2 ## [iView info]
3 ## [Run info]
4 ## [Calibration info]
5 ## [Geometry info]
6 ## [Hardware setup info]
7 ## [Filter settings info]
8 Data (not printed on the file)
9 [Time] [Type] [Trial] [Left/Right Raw X] [Left/Right Raw Y] [Left/Right
   Diameter X] [Left/Right Diameter Y] [Left/Right Mapped Diameter] [Left/
   Right Corneal Reflection X][Left/Right Corneal Reflection Y] [Left/
   Right Point Of Regard X][Left/Right Point Of Regard Y][Head Position X
   ][Head Position Y][Head Position Z][Head Rotation X][Head Rotation Y][
   Head Rotation Z][Left/Right Eye Position X][Left/Right Eye Position Y][
   Left/Right Eye Position Z][Trigger][Auxiliar Data]
```

The generated file includes the subject name in the file name. The connection established between the eye tracker system and Presentation allows the introduction of commands in Presentation that controls the eye tracker. Thus the acquisition start/end, calibration start and data save are functions called into the PCL code of the experiment. To facilitate further synchronization, the current trial and step of the experiment are sent to the eye-tracking system to be recorded in the final file.

4.1.1.3 Biosignals Acquisition Device

The system used to acquire biosignals was biosignalsplux from Plux, Wireless Biosignals S.A. [199]. This is a small and easy configurable device designed for advanced biosignal research. The hub includes 8 generic analogue ports which data collected is sent to a computer via Bluetooth with an acquisition resolution up to 16-bit per channel and a sampling rate that can be up to 4000Hz. The available sensors are:

- Electroencefalogram;
- **Electrocardiogram;**
- Electromyography;
- **Electrodermal activity;**
- Respiration PZL or RIP;
- **Blood Volume Pulse;**
- Accelerometer;
- Temperature;
- Force;
- Light;
- SpO₂;
- Glucose Meter Reader;
- Blood Pressure Reader;
- fNIRS;
- RFID;
- Vaginal Probe;
- Load Cell;
- Goniometer.

For this particular study, only Electrocardiogram (ECG)[80], Electrodermal Activity (EDA)[27] and Blood Volume Pulse (BVP)[197] were acquired.

Although there is an available software to directly record the biosignals, we used an in-house software program that allows the communication between the IGT and the Python programming API of biosignalsplux [198]. The generated file is in npz format with two relevant npy files. One, called "pluxData" includes the data collected from biosignalsplux in which each column contains a signal raw data. The events of the IGT are recorded in "serialEventData" file that are associated with the respective biosignals data frame number.

The generated files include the subject name and start acquisition time in the file name.

4.1.2 Online Surveys

The standard method to evaluate personality is using validated questionnaires. We considered those questionnaires' results as ground truth. Furthermore, the medical decision-making task was also based on an online survey.

To build the online survey we have chosen to use LimeSurvey [236]. This free and open-source on-line statistical survey web app has the flexibility needed for our purpose given that the appearance of the survey is easily edited in the HTML and JavaScript code is simply introduced.

Taking advantage of all subjects need to answer an online survey after each decision making task in this thesis, we decided to inject a JavaScript code to acquire the mouse movements data.

To acquire more reliable pointer interaction data in this context, the question text was configured with high transparency when its area was not hovered (see Figure 4.4). This forces the user to move the pointer when he wants to read the question.

	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
1. Ich bin nicht leicht beunruhigt.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2. Ich habe gerne viele Leute um mich herum.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
3. Ich mag meine Zeit nicht mit Tagträumereien verschwenden.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
4. Ich versuche zu jedem, dem ich begegne, freundlich zu sein.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure 4.4: Example of questions with more text transparency when not hovered.

From this system, two parallel acquisitions were performed: the questionnaires results and the mouse data. These are briefly presented in Figure 4.5.

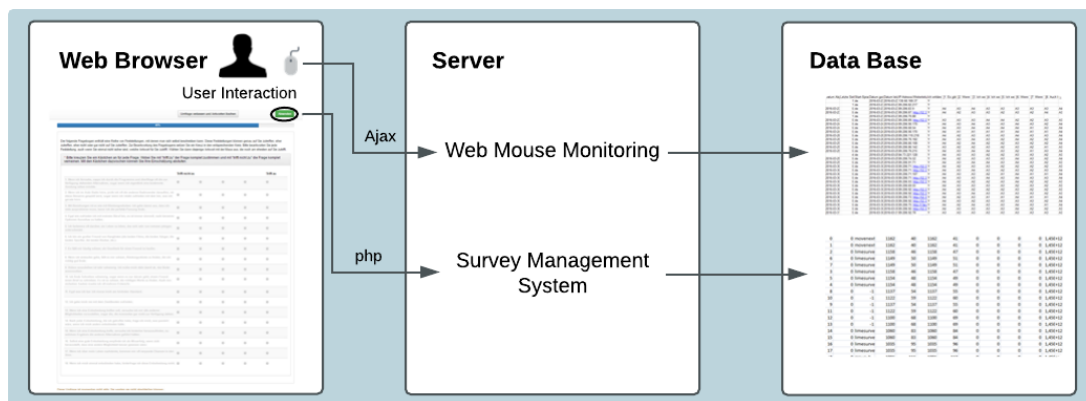


Figure 4.5: Architecture of online surveys data acquisition.

The results of the survey are simply saved on a database via the Survey Management System using *PHP*. The platform LimeSurvey returns a CSV file, quickly configured, as a final result of the survey with the following information:

```
1 Data (not printed on the file)
2 [Start time] [End time] [Answers per questionnaire][Time per questionnaire]
```

In case of mouse movements monitoring, the integration of a JavaScript code (available at <https://github.com/novabiosignals/WebBehaviourMonitoring>) has two alternatives to store the data: on the personal computer or on a remote server. Given that this study involved institutions from different countries, a remote server was the more appropriate option. The data is sent to the server machine via AJAX, a client side technique to asynchronously send and retrieve data from a server, where it is finally recorded as a file in a database, which includes:

```
1 Header (not printed on the file)
2 #[Timestamp] [WBM version]
3 #[Timestamp] [window.screen data]
4 #[Timestamp] [window.navigator data]
5 Data (not printed on the file)
6 [Counter] [Event Code] [ObjectID] [MouseX] [MouseY] [MouseX + ScrollLeft] [
  MouseY + ScrollTop] [Keyboard Code] [Shift] [Alt] [Ctrl] [Timestamp]
```

The name of the file includes the IP address, the survey ID, the step of the questionnaire and the start time of acquisition. These details allow us to synchronize the pointer data with the survey results, matching the IPs address and comparing the times in files.

Throughout the study, and while we were realizing the amount of informative data that can possibly provide insights into web-based navigation behaviour and underlying psychological dimensions (e.g. personality), a novel tool was developed. This tool, called Latent, is a web browser extension capable of simultaneously capture information from different sources while users interact with digital content. A full description of this tool is documented in [46].

4.1.2.1 Personality Questionnaires

To assess the five factors of personality, we used the German version of the NEO-FFI questionnaire [30]. The questionnaire has 60 items and each factor is calculated by averaging 12 items. For each item the answers are given in a five-point Likert scale, where 1 corresponds to "strongly disagree" and 5 to "strongly agree" [163].

4.1.2.2 Medical Decision-Making Task

The Multimorbidity Interaction Severity Index (MISI) [93] was developed in 2017 to be used by physicians for patient-specific assessment and management of multimorbidity. This tool was designed to reliably differentiate hypothetical multimorbid patients in terms of lower versus higher potential for harmful interactions between Disease–Disease,

Drug–Disease, and Drug–Drug Interactions (DDIs). To analyse the medical decision-making, we used MISI II, which was implemented in LimeSurvey and has one medium conflict case, instead of just low and high conflict case with 6 concurrent morbidities, described in Table 4.1. Moreover, rather than a severity scale, this version has three more scales: probability, priority for action and confidence. All scales are four-point Likert scale, with the following scales:

- Severity: 1. None - 4. High;
- Probability: 1. Very unlikely - 4. Very likely;
- Priority for action: 1. No priority - 4. Emergency;
- Confidence: 1. Uncertain - 4. Absolute sure.

To reduce the impact of physicians’ expertise in treating cases of multimorbidity, only novices were recruited.

Table 4.1: Conditions and medications of the three hypothetical patient cases.

Patient	Conditions	Medications
Low conflict case	Iron deficiency anemia Diabetes mellitus type II Panic disorder Arterial hypertension Gastritis Type C Eczema	Ferrous Sulfate Metformin Lorazepam Lisinopril Esomeprazole Moisturizer
Medium conflict case	Pulmonary embolism Aortic valve stenosis Subdural hematoma Renal insufficiency/kidney failure Chronic atrial fibrillation Arterial hypertension	Rivaroxaban Torasemide Esomeprazole Ibuprofen Bisoprolol Lisinopril
High conflict case	Hypertensive emergency Renal failure Iron deficiency anemia Hypothyroidism Rheumatoid arthritis Exacerbated bronchial asthma	Lisinopril Nitroglycerin Iron Sulfate Levothyroxine Morphine Prednisone

4.2 Scientific Computation

Subsequent to the acquisition of all data, it is analysed. To execute this analysis, we used Python language [269]. Diverse python packages were used for numerical manipulation or visualisation: Matplotlib [124] and Seaborn [224] for data visualisation; NumPy [257]

for numerical computation; SciPy [37] for advanced mathematical functions; Pandas [164] for large data structure and statistical tools; Scikit-learn [189] provides machine learning algorithms for supervised and unsupervised learning; Pickle [215] enables serialisation and de-serialisation of a Python object structure, in our case of the models. Besides these, a package called novainstrumentation, provided in classes at Faculdade de Ciências e Tecnologia, Universidade Nova de Lisboa, which contains useful biosignals processing tools, was also used and it is on-line available¹. To analyse non-linear parameters from biosignals, PyEEG [19] and Nolds [268] modules provide functions used in this thesis.

4.3 Studies Design

In this section, the participants and procedures of all studies performed during this thesis are introduced. All participants had to comply with the following conditions:

1. The procedures and experiments were in German, so the participants were native or fluent speakers of Standard German;
2. To keep pointer data consistency, participants were right-handed [10];
3. Participants were healthy, with normal, or corrected-to-normal, vision, no record of neurological or psychiatric illness and no current medication use.

4.3.1 Study 1: Online questionnaires in an uncontrolled environment

4.3.1.1 Participants

A sample of 119 volunteers recruited via a pool of test participants and students of the University of Zurich and the ETH Zurich participated in this study. The participants were aged between 20 and 52 years old ($M=25.4$; $SD=5.4$; 18 male).

4.3.1.2 Procedure

In this study, the participants were just invited to respond to an online survey. Figure 4.6 shows the steps that the survey comprises. First, the informed consent is presented, according to the guidelines of the Declaration of Helsinki, about the context of the survey in the welcome page. Participants must confirm in "Agreement Page" that wants to participate in this study and, only then, the personality assessment, the Neuroticism items of NEO-FFI, was presented. In "Personal Information" participants could write their name, email and phone number.

The procedure was not controlled by an expert. The subject received an email with the link to the online survey and it is their own decision when and where to answer.

¹<https://github.com/hgamboa/novainstrumentation>



Figure 4.6: Sequence of steps in the survey.

4.3.2 Study 2: Simulated Decision Making Task

4.3.2.1 Participants

A sample of 88 volunteers participated in this study recruited from the University of Zurich via flyers. The participants were aged between 18 and 35 years old (44 male). They were paid with 20 Swiss Francs or the equivalent credit points, which are mandatory for master students, for participation. The participants reported no gambling problems.

4.3.2.2 Procedure

In this study, the participants were tested individually in a small, sound-attenuated, dimly lit experimental room. The experiment was conducted in three phases: First, informed consent and demographic data were collected on paper. Then, the participant played the IGT and finally, the personality data, i.e. the NEO-FFI Inventory, was collected in an online survey, which steps are the same presented in Figure 4.6. This time, the complete version of the NEO-FFI was used. The steps of this procedure are presented in Appendix C.

This procedure was controlled by master students of psychology degree of the University of Zurich.

4.3.3 Study 3: Simulated Decision Making Task with Psychophysiological Data Record

4.3.3.1 Participants

A sample of 79 volunteers participated in this study recruited from the Swiss Federal Institute of Technology and the University of Zurich using a mailing list. The participants were aged between 18 and 34 years old ($M=23.9$; $SD=4.2$; 18 male). They were paid with 20 Swiss Francs or the equivalent credit points for participation. No gambling problems were reported by the participants.

4.3.3.2 Procedure

In this study, the procedure was very similar to the previously described in 4.3.2.2. Once collected the demographic data and signed the informed consent, the biosignals sensors were placed and the eye-tracker support for the head was prepared. A 1 minute resting baseline was performed at the beginning of the experiment to facilitate laboratory adaptation. Then the participant played the IGT and the personality data, i.e. the NEO-FFI

Inventory, was collected in an online survey (see Figure 4.6). The online survey used to collect the personality data is presented in Appendix C.

Biosignals were acquired with the Biosignalsplux with a sampling frequency of 1000 Hz and the eye-tracking data with a sampling frequency of 60 Hz. The number of bits used was 12 bits for each channel of the Biosignalsplux ADC. The EDA electrodes were placed over the left-hand palm since the palms are one of the places with the highest percentage of sweats glands of the human body [89] and the participants are consistently right-handed. The BVP sensor was placed on the index finger of the left hand and the ECG electrodes on the chest of the participant. Ag/AgCl electrodes with surface diameter of 7 mm were used in EDA and ECG acquisitions. The biosignals and eye-tracking acquisition is triggered by the start of the decision-making task experiment.

4.3.4 Study 4: Medical Decision Making Task

4.3.4.1 Participants

A sample of 13 volunteers participated in this study. Participants were physicians from the University Hospital of Zurich with a maximum of 4 years of experience in internal medicine. The participants were aged between 27 and 34 years old ($M=32.0$; $SD=1.9$; 5 male).

4.3.4.2 Procedure

In this study, the participants were tested individually in a small, sound-attenuated, dimly lit experimental room. The experiment was conducted in four different moments because of the extensive duration of each case. First of all, informed consent and demographic data were collected on paper. Then, general instructions about the study are provided before starting the first case. The cases are analysed in random order and on different days and hours. For each case, information on the patient case and examples of the DDIs assessment scales are provided on paper and the participant has these documents during the test. The DDIs rating is made on an on-line survey structure, as well as the general opinion about the case. At last, the participant modifies the current medicines in the case on paper. After solving the three cases, the participant is requested one last time to collect the personality data, i.e. the NEO-FFI Inventory, in an online survey. The order of the computerised steps are presented in Figure 4.7. The online survey used to collect the personality data is presented in Appendix C and the steps of the whole procedure are presented in Appendix D, with the example of case 1.



Figure 4.7: Sequence of steps in the MISI.

TECHNICAL TOOLS

This chapter includes a description and explanation of the processing tools applied to extract features from the data acquisition systems described in Chapter 4. In diagram 5.1 is presented the main purpose of this chapter in this thesis: to explain how data is prepared using the outputs of the "Data Management", how it is processed and interpreted regarding the experiments conducted. For each data set and respective processing tools, at least one output is returned. Throughout this chapter, it is explained in detail what files are needed for each processing step and what are the correspondent outputs.

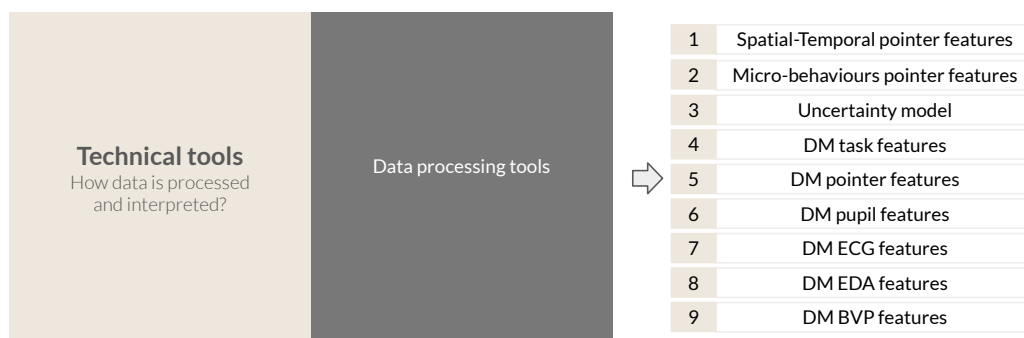


Figure 5.1: Details about what will be explained and what are the outputs of the Chapter "Technical Tools" in the context of this thesis.

5.1 Survey Pointer Processing Tools

This section will present the processing tools applied to the pointer interaction in online surveys. It will cover a detailed explanation of all the procedures from the original files, presented in 4.1.2, to the final set of features extracted.

Previous studies do a temporal and spatial analysis of the pointer movement extracting features such as the velocity of the movement [13], or to compare straight and curved movements [136, 225]. Regarding the context of data acquisition and which are the interest areas, hovering patterns [11, 123, 136], long pauses [13, 136, 225] or direction changes [276] are examples of more complex analysis. Although the basic mouse analysis is based on the cursor position or clicked elements, behaviours like hesitation, frustration, assertivity, attention or abandonment are also extracted to perform web pages usability tests [54, 59, 122, 171].

To the best of our knowledge, no previous studies analysed the pointer interaction in the specific context of online surveys. For this reason, we explored which alternative paths could a user follow while answering an online questionnaire and, as a result, we created a sequence to demonstrate our conclusions. To assure the correct extraction of features, given that several bugs were reported during the data analysis, files from Study 1 was used to pre-process the data and validate spatial-temporal features. The visualization of the data from Study 2 was useful to explore and identify micro-behaviours that give rise to more informative features. Although the majority of micro-behaviours extracted were never mentioned in previous work, some of them were inspired in features applied in different contexts.

5.1.1 Interaction Sequence for Questionnaires

To determine which features could be extracted from the pointer interaction dynamics, with knowledge-value about the individual, it is crucial to contemplate and understand possible behavioural patterns of a subject while answering an online questionnaire. This section exposes the various steps involved in a questionnaire reply that helped us to infer contextual features relevant for the individual personality. Throughout the explanation of the different stages, the arose features are presented.

Figure 5.2 shows the first step, which is entering the survey. It is possible to close the webpage and leave the survey or to go to the first question group and then to the next group.



Figure 5.2: Survey diagram.

Inside the question group (Figure 5.3), the subject could go to every question to answer that. When all questions are answered, he can submit the survey.

As already referred, when the subject decide to go to a question for then provide an answer, he can just move the mouse or scroll in that direction, as shown in diagram 5.4. From scroll, it is possible to extract the number of scrolls done and the number of items scrolled as features.

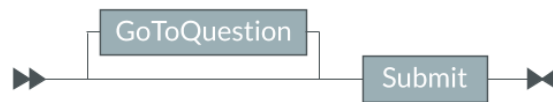


Figure 5.3: Question Group diagram.



Figure 5.4: Go to question diagram.

The process involved in answering a question, represented in Figure 5.5 is the most complex and from where we can extract more contextual features. There are different alternatives when answering a question. The most complete approach is to read the question, move the pointer to the answer and select it. After this, if the subject moves the pointer to another answer and selects a different answer, it is considered an event of correction within an item. In case the subject goes and answers to another question or questions but comes back to change the previous chosen answer, it is considered an event of correction between item. After proceeding to the next question, the subject could also turn back and do a revisit in a previously answered question, which is the event of going back to a previous question without changing the answer.

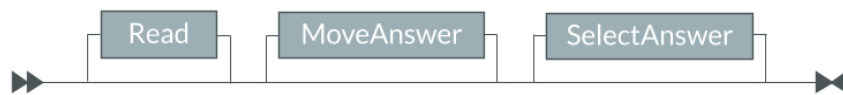


Figure 5.5: Answer question diagram.

At last, the survey submission is only possible when every question is filled. Otherwise, a warning appears.

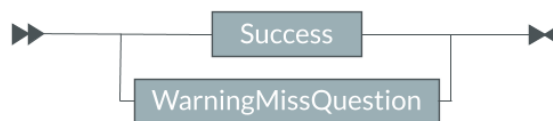


Figure 5.6: Submit diagram.

5.1.2 Pre-processing Data

Some of the original pointer files have unexpected data collection errors that need to go through a pre-processing phase to then be correctly analysed. Being carried out in an uncontrolled environment, it is Study 1 that is more susceptible to errors given that no restriction of time or device was imposed. Therefore, the files from Study 1 were used to identify errors and validate the pre-processing procedures.

5.1.2.1 Server File Correction

In terms of the mouse raw file acquired in the server, the existing problems and corrections implemented were:

1. Two different data lines are together, a paragraph is done between the two;
2. The counter of the data lines are not in the correct order;
3. Files without the number of frame column are identified;
4. If different files are from the same questionnaire and subjects, they are concatenated;
5. Repeated positions (x, y) in consecutive data lines are removed;
6. Repeated timestamp in consecutive data lines are removed;
7. Data lines with *Not A Number* values are removed.

5.1.2.2 Device Identification

The usage of an online survey requires the identification of the device in use because the target desired (pointer movement) is lost in touch screen devices. This way, the data from touch screens' devices were not considered. To identify these devices, regarding that there is no pointer movements (represented as 0 in the pointer file), the predominant *EventCode* in touch devices files will be 1, as it is the identification of clicks. Then, the file is not considered if the ratio between the events where the pointer is moving ($event = 0$) and the events where the mouse is down ($event = 1$) is less than 2:

$$\frac{\#events = 0}{\#events = 1} < 2$$

5.1.2.3 Data Validation

As already referred, there are some possible errors and corrections that need to be applied to each server file to correctly extract some information from the data. To ensure that everything is working properly and that we are returning quality results, an output CSV file was generated with the following details described.

- Original number of subjects (*#original subjects*);
- Number of subjects with correct mouse data (*#subjects*);
- Number of subjects using touch screen devices (*#touchscreen files*);
- Percentage of files with missing samples (*%files without samples*);
- Mean of percentage of samples missing (*%lost samples*);
- Percentage of files that are split (*%concatenated files*).

The result of the validation file from this study is presented in Table 5.1.

Table 5.1: Validation file output from Study 1.

Result	Output
# original subjects	119
# subjects	89
# touch screen	24
% files without samples	26
% lost samples	0.0087
% concatenated files	1.7

5.1.3 Spatial-temporal Information

The result of the pointer interaction can be interpreted not only in the temporal domain but also in the spatial domain. Bearing this in mind, the data preparation for each of the approaches was required to extract the respective features. Basically, this corresponds to Output 1 of the Chapter "Processing Tools" in the diagram of Appendix A. The server pointer files from Study 1 (Output 2 of the Chapter "Data Management" in A) were used to assess and validate the features extraction from the mouse interaction in terms of time and space.

5.1.3.1 Spatial Information

In the spatial domain, the pointer interaction in the questionnaire is analysed as a single path, from the beginning until the end of the questionnaire.

To smooth the spatial signal, a spatial vector s representing the cumulative length along the path, between two mouses positions, is calculated:

$$s_i = \sum_{k=1}^i \sqrt{\Delta x_k^2 + \Delta y_k^2}, \quad i = 1 \dots n - 1,$$

$$\Delta x_i = x_{i+1} - x_i, \quad \Delta y_i = y_{i+1} - y_i$$

A cubic spline interpolation is then applied in order to produce a curve signal with a space interval equal to the mean value of the length variance:

$$\alpha = \overline{\Delta s},$$

$$\Delta s_i = s_{i+1} - s_i$$

An example of this pre-processing procedure is shown in Figure 5.7, in which is exemplified a fraction of a movement and a comparison between the original signal and the interpolated result.

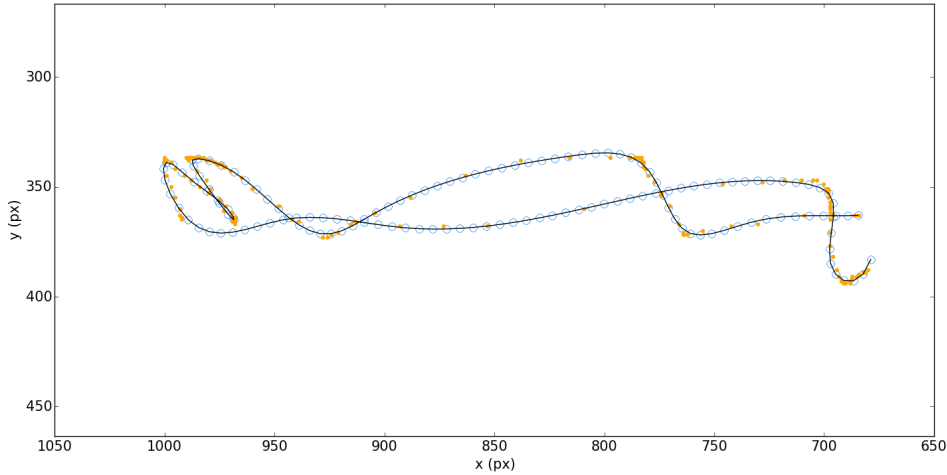


Figure 5.7: Spatial signal x-y representation in pixels. The orange dots (●) represent the signal extracted from the pointer movement, the blue dots (○) represent the signal with constant spacing and the black line (-) represent the curve from interpolation.

The **questionnaire path length** (\bar{s}) is easily extracted from s , $\bar{s} = s_{n-1}$ and expressed in pixels. To generalize this measure to other questionnaires, \bar{s} is divided by the number of items.

To calculate the **angle** vector (θ) we used the following expression:

$$\theta = \arctan\left(\frac{\Delta y}{\Delta x}\right) \quad \text{rad},$$

however, to avoid the radian phase discontinuities near $-\pi$ and π , we added multiples of $\pm 2\pi$:

$$\theta_i = \arctan\left(\frac{\Delta y_1}{\Delta x_1}\right) + \sum_{j=1}^i \min\left\{\Delta \arctan\left(\frac{\Delta y_j}{\Delta x_j}\right) + 2k\pi\right\} \quad k \in Z$$

The **curvature** (c) is inversely proportional to the circle's radius created at the tangent point of the path in study. The curvature is expressed by:

$$c = \frac{x'y'' - y'x''}{(x'^2 + y'^2)^{3/2}}$$

We have interest only in the absolute values of angles and curvatures. The rate of change in curvature (c') is given by the expression:

$$c' = \frac{\Delta c}{\Delta s}$$

Figure 5.8 represents the angle and curvature results from the path represented in 5.7.

From each stroke defined, we can calculate its **length** (s_{stroke}) and **straightness**, which is defined as the ratio of the Euclidean distance between the start and end of the

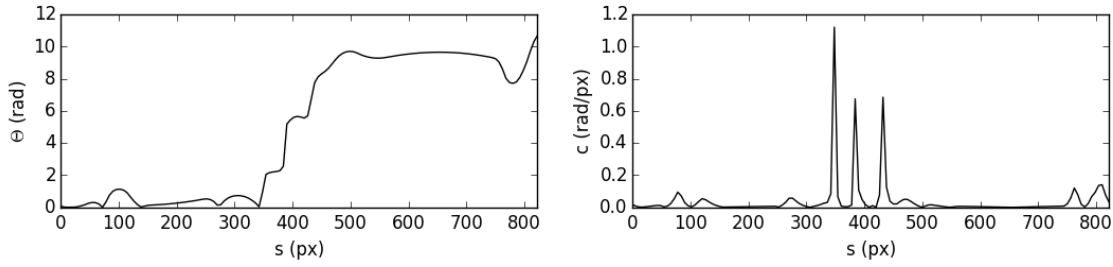


Figure 5.8: In the graphic at left it is represented the angles in radians over distance in pixels and the graphic at right represent the curvature in radians/pixels over distance in pixels.

stroke and the total distance travelled (length):















$$straightness = \frac{\sqrt{(x_1 - x_n)^2 + (y_1 - y_n)^2}}{s_{n-1}}$$

The tremors in the user movements were measured by **jitter**, which corresponds to the ratio between the smoothed path length and the original path length:

$$jitter = \frac{s'_n}{s_{n-1}}$$

Table 5.2 summarizes and describes the final set of spatial features. Since some features are statistically analysed, the total number of spatial features is 22.

Table 5.2: Details about features extracted in spatial domain. Distribution and range values from Study 1. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Symbol	Feature	Name	Unit	Distribution	Range	Note
	Length	\bar{s}	<i>px</i>		$[2.8 \times 10, 4.0 \times 10^3]$	0
	Angle	θ	<i>rad</i>		$[-3.1 \times 10, 6.2 \times 10]$	1
	Curvature	c	<i>rad.px⁻¹</i>		$[-8.2 \times 10^2, 6.6 \times 10^2]$	1
	Variation Curvature	c'	<i>rad.px⁻²</i>		$[-4.3 \times 10^5, 8.3 \times 10^5]$	1
	Strokes Length	s_stroke	<i>px</i>		$[2.2, 9.0 \times 10^3]$	1
	Straightness	<i>straightness</i>	-		$[8.1 \times 10^{-3}, 1.0]$	0
	Jitter	<i>jitter</i>	-		$[2.8 \times 10^{-1}, 9.8 \times 10^{-1}]$	1

5.1.3.2 Temporal Information

In the temporal domain, the interaction in the questionnaire was not considered as a whole but as a set of strokes, depending on the interval between sequential movements. When a subject takes more than k_{stroke} seconds to move the pointer, the movements before and after that pause were considered strokes.

In order to have a signal with equal temporal spaces, we applied a cubic spline interpolation to each stroke. The interval delimited is proportional to the mean variance of time:

$$\alpha = k_{timeinterp} \times \overline{\Delta t},$$

$$\Delta t_i = t_{i+1} - t_i$$

Figure 5.9 exemplifies the curve interpolated from the x and y original signals. It is possible to identify different strokes, pauses and well defined different intervals of interpolations for each stroke.

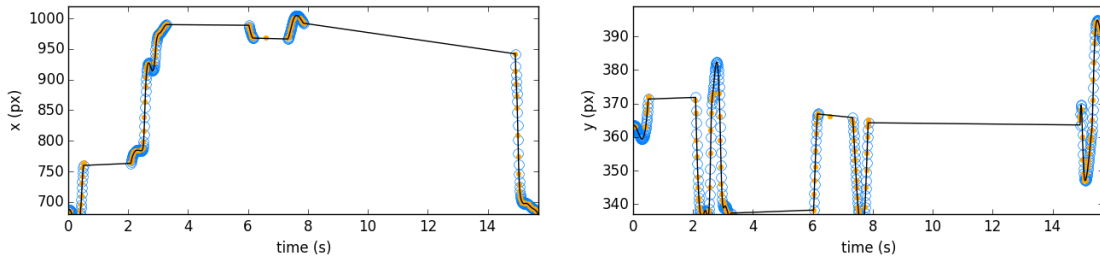


Figure 5.9: Temporal signal x-y representation in pixels. The orange dots (●) represent the signal extracted from the mouse movement, the blue dots (○) represent the signal with constant and defined spacing and the black line (-) represent the curve from interpolation.

The **total time** of the questionnaire (t_{total}) was easily extracted from t , $t_{total} = t_{n-1}$ and expressed in seconds. To generalize this measure to other questionnaires, t_{total} was divided by the number of items.

To correctly calculate the velocity of the mouse movement, a vector which includes the velocity values when the mouse moves and consider the velocity zero when no movement need to be computed. It is named **velocity** (v_t).















From temporal information we also extract the **horizontal velocity** (v_x), **vertical velocity** (v_y), **acceleration** (a), **jerk** (a') and **angular velocity** (w):

$$v_x = \frac{\Delta x}{\Delta t} \quad v_y = \frac{\Delta y}{\Delta t} \quad a = \frac{\Delta v_t}{\Delta t}$$

$$a' = \frac{\Delta a}{\Delta t} \quad w = \frac{\Delta \theta}{\Delta t}$$

Table 5.3 summarizes and describes the final set of temporal features. Regarding that some features are statistically analysed, the total number of temporal features is 25.

Table 5.3: Details about features extracted in temporal domain. Distribution and range values from Study 1. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Symbol	Feature	Name	Unit	Distribution	Range	Note
	Total time	t_{total}	s		$[3.5, 2.8 \times 10^5]$	0
	Temporal Velocity	v_t	px/s		$[0.0, 1.7 \times 10^5]$	1
	Horizontal Velocity	v_x	px/s		$[0.0, 1.1 \times 10^5]$	1
	Vertical Velocity	v_y	px/s		$[0.0, 1.6 \times 10^5]$	1
	Angular Velocity	w	rad/s		$[-9.1 \times 10^1, 1.1 \times 10^2]$	1
	Acceleration	a	px/s^2		$[-1.7 \times 10^8, 1.7 \times 10^8]$	1
	Jerk	$jerk$	px/s^3		$[-1.7 \times 10^{11}, 1.7 \times 10^{11}]$	1

5.1.4 Micro-behaviours Information

This section is a result of a deep analysis of the mouse interaction in the context of online surveys. The described features are related to the task and, the more complex ones, resulted from a visual analysis of different subjects. We call these features micro-behaviours, bearing in mind that they represent a distinct behaviour and that they were observed in several subjects. Basically, this part of the work corresponds to Output 2 of the Chapter "Processing Tools" in the diagram of Appendix A. In contrast to the spatial-temporal features, the server pointer files are, in this case, from Study 2 (Output 4 of the Chapter "Data Management" in A). We decided to use these files for this purpose because this study was performed in a controlled environment and, considering that these are not generic features, the existing noise in uncontrolled environment data could generate distorted assumptions. Furthermore, the combination of some of the identified mouse patterns led us to build an uncertainty model, that returns the uncertainty felt by each subject in each item of the questionnaire. For this model to be subsequently applied and ensure consistency it is important to use a controlled environment and, therefore, Study 2.

The first reported behaviour was called **overview** ($\#overviews$). This is characterized by, at the beginning of the survey, scrolling the cursor over a wide area in direction to the bottom of the survey getting an overview of it, to get an overall idea of the number

of questions, the length of the survey or the types of questions. A visualization of this behaviour is represented in Figure 5.10, in which the mouse y coordinate is represented over time. The first question is at the top of the plot (small y values) and, moving forward through the next questions, the y increases. At the beginning of the questionnaire, this subject goes to the end of the survey and then comes back to the first questions. Computationally, when suddenly the user crosses more than one-quarter of the items of the whole questionnaire, it was considered an overview. As seen in Figure 5.10, this behaviour can also occur after one minute and two minutes of interaction, but never so far as the first time and, for this reason, only if a big number of items are crossed (at least one-quarter) it was considered an overview. The final feature corresponds to the number of overviews in a questionnaire.

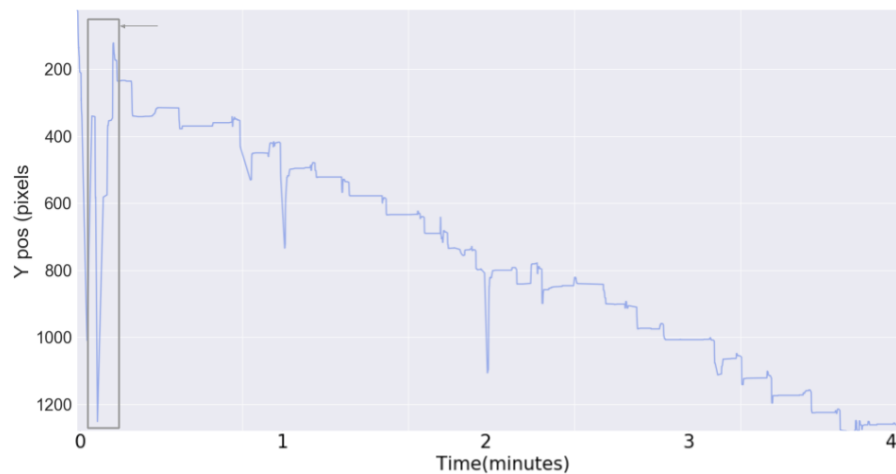


Figure 5.10: Representation of the y-axis of the pointer movement over time. The rectangle area corresponds to an overview pattern.

The second observed behaviour was the **skip pattern** (*#skips*). When answering the survey some subjects would not have a linear behaviour of following the natural order of questions. In fact, some subjects would skip questions and answer in an unnatural order. This behaviour is represented in Figure 5.11, in which the user, after answering question two, starts to answer from question 14 to the previous questions. When the user is back to question 3, goes again to the end and answer question 18 until question 15. To compute this feature, we verified the order of the items answered, without considering further corrections, and if the user moves back to a previous question, it means he skipped that item and, therefore, it was considered a skip. The final feature corresponds to the number of skipped items and, given that it is related to the number of items of the questionnaire, we normalized this feature dividing by the total number of items.

Analysing pointer movements, pauses of movement should be regarded. There are three features that can be extracted from this perspective: time of interaction, time of pauses and number of strokes. The **time of pauses** (t_pauses) is a vector with the interval

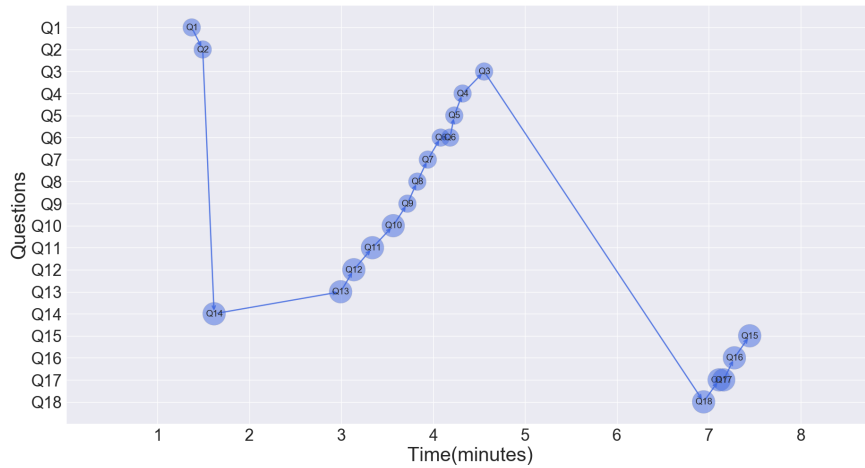


Figure 5.11: Representation of the questions answered over time. This user is an example of skip behaviour.

of times that people remain without interaction more than k_{pause} seconds between strokes and the **number of strokes** ($\#strokes$) corresponds to the number of times that people move the mouse between pauses. The **time of interaction** is the total time that people are moving the mouse, excluding from the total time the time of pauses. In Figure 5.12 there are represented in blue the intervals of time when the subject is paused ($k_{pause} = 1\text{ second}$) and it is possible to identify 5 strokes and 4 pauses in this example. The number of strokes and time of interaction are normalized according to the length of the questionnaire, and therefore, divided by the total number of items.

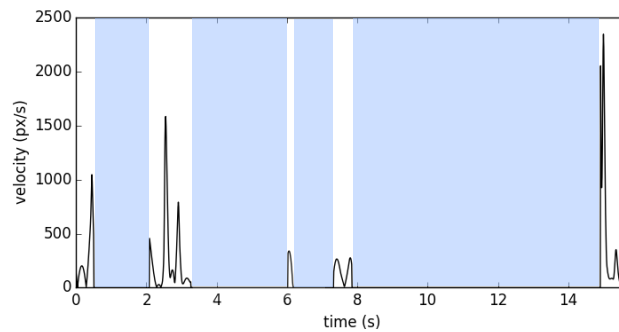
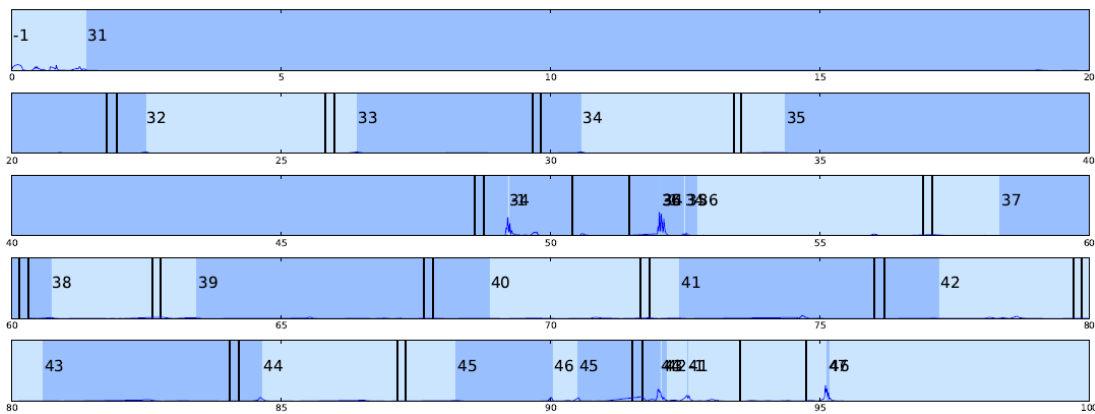


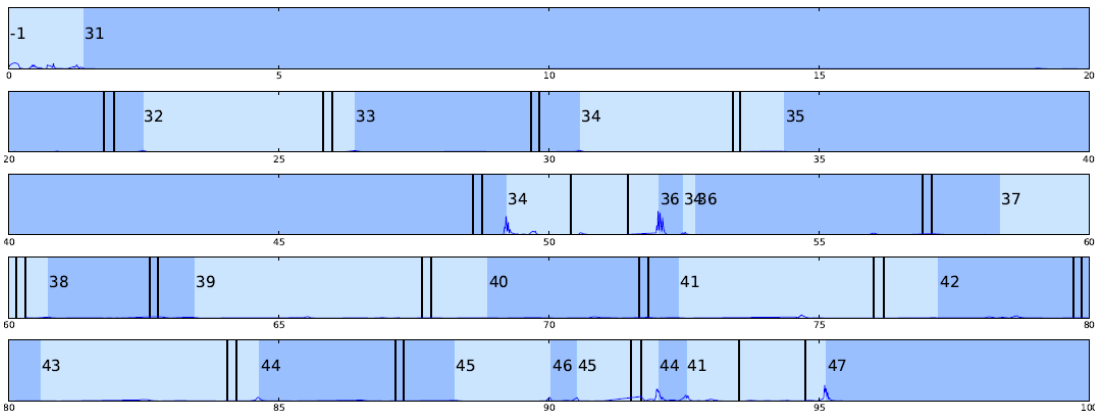
Figure 5.12: Velocity in time.

All the following described features need a previous correction to verify if the subjects are not wandering around the page but remain in the same question or if they just go down in page and come back to the same item. We call this zapping events and, in spite of being considered as features, we removed them from the signal for further analysis. The impact of these variables is represented in Figures 5.13a and 5.13b, in which is represented the temporal velocity in pixels/second in y-axis and time in seconds in x-axis. It has a blue and light blue background to distinguish the change of item, which is numbered in the graphic when it happens. The vertical black lines represent the mouse

down and up (clicks). We can compare both figures and notice that Figure 5.13b do not consider the zapping items, which could produce results with errors. It is easily noticeable at second 53 and second 93 that there are less rapid changes of items. Based on the time that people remain inside an item area, a zapping item is classified when this interval of time is less than k_{zapp} seconds. When a subject is scrolling, many zapping items are detected and, therefore, we classified this event as a zapping event and considered the items that were crossed by the pointer. From the whole questionnaire we extracted the **number of zapping events** ($\#zapp$) and the **number of zapped items** in all zapping events ($\#items_zapped$). The last feature was normalized, being divided by the total items in the questionnaire.



a Example of a survey's response dynamics with zapping events.



b Example of a survey's response dynamics with zapping corrections.

Figure 5.13: Representation of the difference of results when applied the zapping correction. These show the signal of velocity over time in seconds, the change of question is noted by the change of colour, between blue and light blue, and at the beginning of the new question it is the number of the item. The black vertical lines are the mouse click (one for mouse down and one for mouse up). With fast changes the number of items is aligned vertically.

The spent **time in each item** is kept in a vector (t_item), which with the zapping corrections gives us a more realistic information, ignoring short times caused, for example,

by scroll actions.

Sometimes, external factors could interrupt the subject focus on the survey, or the subject could abandon the survey for a while to answer a telephone call, for example. We considered the **number of abandons** ($\#abandon$), defined by:

$$Abandon = k_{abandon} \times mean(t_{item})$$

The sum of the **time of abandons** ($t_{abandon}$) was also considered as feature. When an abandon event is identified, the respective time value is removed from t_{item} . This way, this vector will contemplate only the time spent to answer a question, having just normal situation values.

The t_{item} consider only the time between the mouse enter the item and leaving it. To consider the total duration that the mouse was inside each item, we calculated the **accumulated time** (t_{accum}).

When the mouse is inside a question, we found two different ways of reading the statement: some people move the mouse to the text area, while reading the question, while others just move the mouse around the answers area. To identify this behaviour of **hovering the text** ($\#hover_text$), after defining the width of the text of the question, the x mouse coordinates can be associated to questions or answers area. The associated feature was the accumulative time that the subject was in the questions area. To be independent of the questionnaire size, this feature was divided by the number of items.

Thinking about hovering the answers area, instead of the text area, there are two features: number of hovered answers and selected answer ratio. The **number of hovered answers** ($answer_hover$) corresponds to the number of hovered answers divided by the total number of possible answers. The **selected answer ratio** ($answer_ratio$) is defined by the duration of hovering the final answer, in relation to the total time in the answers' area.

In relation to the click after being inside the question, the **time before click** (t_{bef_click}) was calculated and it is the sum of all the time intervals in a question until the first click, considering previous time intervals in case the person enters the question for more than one time. The **pause before click** ($pause_bef_click$), which is the time interval that a person remains stopped before clicking an answer, was also computed. If the participant clicks more than once in a single question (to correct a previous answer), this value is averaged. The time between a click in and click out to choose an answer was also calculated and named **time click** (t_{click}).

Because some users move the mouse around the final answer, the distance from the path inside a question to the selected answer was also computed. This **distance from answer** ($distance_answer$) is given by the equation 5.1, where x_{answer} and y_{answer} are the x and y coordinates of the question's last click.

$$Distance\ from\ answer = \sqrt{(x_i - x_{answer})^2 + (y_i - y_{answer})^2}, \quad i = 1, \dots, n - 1 \quad (5.1)$$

While thinking about the answer, some subjects change the mouse horizontal direction, which we called $<-turns$ and is represented in Figure 5.14. This was calculated by the horizontal trajectory's derivative changes from positive to negative values or vice-versa.

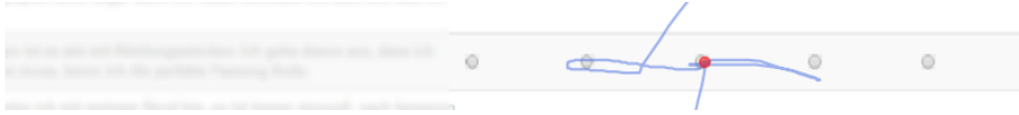


Figure 5.14: Representation of $<-turn$ pattern. In blue is presented the mouse movement and in red the mouse click.

When the individual selects one option, but keeps interacting inside the item and decides to change the option selected to another answer, we defined this behaviour as **correction within item** ($\#correc_within_item$).

Before leaving the question, the interval of time spent between click and go to the next item was calculated and named **inter-item interval** ($\#inter_item_interval$).

A different approach of correcting the previous answer is the **correction between item** ($\#correc_between_item$). In this case, the person selects an answer, move forward to the next questions, and after answering at least one more question, decides to go back and change the previous answer given.

Similar to the last explained behaviour but, instead of changing the previous answer, keeping it, we have the **revisit** ($\#revisits$). This is exemplified in Figure 5.15, in which the user has revisited a prior answer (from question 14 to question 3) which was at the top of the survey. Interestingly, after answering the first time to question 3, this subject responded to question 4 and came back to question 3, that has changed three times the option previously answered. The revisit was around three minutes after these changes.

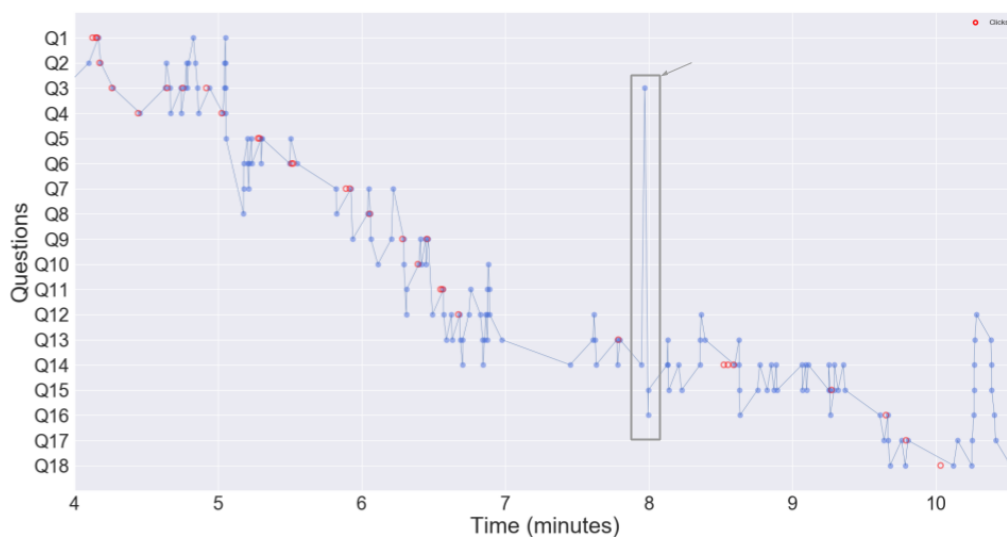


Figure 5.15: Representation of the questions where the mouse is located over time. The red circles represent the mouse clicks. The rectangle area corresponds to a revisit behaviour.

In relation to the corrections, the **correction time** (t_{correc}) was calculated by the sum of all the time intervals in a question from the first click until the last click (last correction). If there is not any correction, this value is zero.











Table 5.4 summarizes the final features and classifies them. When the note is equal to 1, this variable could be statistically analysed and return 4 values: maximum, minimum, mean and standard deviation. With these in consideration, in the end, there are 60 variables.

5.1.5 Uncertainty Detection

The level of uncertainty while answering a question corresponds to the difficulty that a respondent may find to make a rating about a statement. This could be caused by multiple factors: 1) the subject may not have thought about the statement previously; 2) have difficulty retrieving from memory all relevant information; 3) feel unsure about which response alternative best matches the respondent's subjective point of view; 4) find it difficult dealing with many similar statements in a questionnaire; or 5) the subject may also tend to be self-uncertain or indecisive [79, 186, 206, 223]. To compute this feature, 24 features extracted from mouse behaviour were selected for model training and testing. Using logistic regression and k-fold cross-validation, the predictive model of uncertainty achieved an estimated performance accuracy of 89% and this was used to return the number of uncertainty items for each subject. More information about this model is in Appendix B.







































The last regarded feature was, therefore, the number of items in which the subject was uncertain ($\#uncertainty$), that ranges from 1.6×10^{-2} to 1.

Table 5.4: Details about features extracted by the identification of micro-behaviours. Distribution and range values from Study 2. Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Symbol	Feature	Name	Unit	Distribution	Range	Note
	Overview	$\#overviews$	-		[0, 2]	0
	Skip	$\#skips$	-		$[0, 1.6 \times 10^{-1}]$	0
	Time of Pauses	t_{pauses}	s		$[1.0, 3.8 \times 10^1]$	1
	Strokes	$\#strokes$	-		[0.4, 2.5]	0
	Time of Interaction	$t_{interaction}$	s		[0.1, 8.1]	0

(To be continued)

CHAPTER 5. TECHNICAL TOOLS

Symbol	Feature	Name	Unit	Distribution	Range	Note
	Zapping Events	<i>#zapp</i>	-		[0, 46]	0
	Items Zapped	<i>#items_zapped</i>	-		[0, 2.3]	0
	Time per item	<i>t_item</i>	s		[0.0, 1.8×10^2]	1
	Abandons	<i>#abandon</i>	-		[0, 12]	0
	Time of abandons	<i>t_abandon</i>	s		[0, 1.2×10^2]	1
	Accumulated time	<i>t_accum</i>	s		[0.6, 1.8×10^2]	1
	Hovering text	<i>#hover_text</i>	-		[0.1, 0.3]	0
	Hovered answers	<i>#ans_hovered</i>	-		[0.2, 1]	1
	Selected answer ratio	<i>answer_ratio</i>	-		[9.9×10^{-3} , 1]	1
	Time before click	<i>t_bef_click</i>	s		[0, 51]	1
	Pause before click	<i>pause_bef_click</i>	s		[0, 17]	1
	Click Time	<i>t_click</i>	s		[0, 5]	1
	Distance from answer	<i>distance_answer</i>	px		[2.2, 6.5×10^2]	1
	<-turns	<i><-turns</i>	-		[0.1, 6.9]	0
	Correction Within Item	<i>#correc_within_item</i>	-		[0, 0.5]	0
	Inter-item Interval	<i>inter-item_interval</i>	s		[2.4×10^{-2} , 1.8×10^2]	1
	Correction Between Item	<i>#correc_between_item</i>	-		[0, 0.9]	0
	Revisits	<i>#revisits</i>	-		[0, 4.8]	0
	Correction time	<i>t_correc</i>	s		[0, 179]	1

5.2 Decision-making Task Processing Tools

This section will present the extracted features from the files resulted from the IOWA Gambling Task (IGT). These files correspond to output 5 and 8 of the Chapter "Data Management" and the set of features obtained by these tools are the output 4 of this chapter (see diagram A).

The features related to the IGT are easily extracted directly from the collected data files and, consequently, do not require extensive processing.

Taking into consideration the conventional learning profile across five blocks of 20 trials, features are also calculated for each block. In Table 5.5 are described all the features, in which ## means this feature is extracted from the entire game (TT), from block 1 (B1), from block 2 (B2), from block 3 (B3), from block 4 (B4) or from block 5 (B5), B# means this feature is only extracted for each block and TT means this feature is only extracted once, from the total time of the game. In total, 132 features are extracted from the IGT.

From the *logfile* of the IGT, when the event "fixed" is returned, the fixation phase starts, which corresponds to the beginning of the trial. In the event "feedback", information about the deck selected and the result of that selection is returned and, with the segmentation of each trial, all the features are quickly calculated. The feature BX_total_money is only computed for each block, given that the final money in block 5 is the same as the entire game final money.

To assess the participant performance, which is given by choosing the "good" decks, we calculated the ratio between "bad" decks and "good" decks selection, which we called *inefficiency*.

In relation to *TT_no_choice*, the restart is detected when a "fixed" event occurs twice, without a "feedback" event in the middle. Because it is not expected that people exceed the 7 seconds limit to restart the choice phase, we only considered this feature for the entire game.

5.3 Decision-making Task Mouse Processing Tools

This section will present the extracted features from the mouse movements file resulted from the IGT. This file corresponds to output 9 of the Chapter "Data Management" and the set of features obtained by these tools are the output 5 of this chapter (see diagram A).

The type of data of the mouse interaction in this context is similar with the data extracted from the mouse interaction in the online survey and, consequently, the processing tools applied to extract features from the temporal and spatial information are the ones described in section 5.1.3. In this context, there is no need to be concern about zapping events because there is no way of scrolling through the page, or abandons because the participant is in a controlled environment. In consistency with the features extracted in 5.2, these were also extracted for the five blocks of the IGT and for the entire game.

Table 5.5: Features extracted from the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
<i>B#_total_money</i>	<i>CHF</i>	current money	0
<i>##_reward</i>	<i>CHF</i>	sum of rewards	0
<i>##_penalty</i>	<i>CHF</i>	sum of penalties	0
<i>##_RT</i>	<i>s</i>	reaction time	1
<i>##_RT_reward</i>	<i>s</i>	reaction time after a reward	1
<i>##_RT_penalty</i>	<i>s</i>	reaction time after a penalty	1
<i>##_highest_reward</i>	<i>CHF</i>	highest reward value	0
<i>##_highest_penalty</i>	<i>CHF</i>	highest penalty value	0
<i>##_deck1</i>	-	number of deck 1 selections	0
<i>##_deck2</i>	-	number of deck 2 selections	0
<i>##_deck3</i>	-	number of deck 3 selections	0
<i>##_deck4</i>	-	number of deck 4 selections	0
<i>##_inefficiency</i>	-	ratio between bad decks and good decks selection	0
<i>TT_no_choice</i>	-	number of restarted choice phases	0

As a result, the total number of spatial features is 132 and the total number of temporal features is 150.

In terms of context, three features are identical to the presented in 5.1.4: time of pauses, number of pauses and time of interaction. The remaining features are related to the decks. In total, from the context are extracted 186 features (see Table 5.6).

Table 5.6: Contextual features extracted from the mouse movements in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
<i>##_t_pauses</i>	<i>s</i>	Time of mouse movements pauses	1
<i>##_nr_pauses</i>	-	Number of mouse movements pauses	0
<i>##_t_interaction</i>	<i>s</i>	Total time of mouse moving	0
<i>##_decks_hovered</i>	-	Number of decks hovered	1
<i>##_t_sel_decks</i>	<i>s</i>	Time hovering the selected deck	1
<i>##_t_other_decks</i>	<i>s</i>	Time hovering the not selected decks	1
<i>##_t_out_decks</i>	<i>s</i>	Time hovering the area outside the decks	1
<i>##_sel_deck_ratio</i>	-	Ratio between the time hovering the selected deck and the total duration of the trial	1
<i>##_alterations</i>	-	Number of changes from hovering a deck to hovering another	1
<i>##_total_alterations</i>	-	Total number of alterations	0

5.4 Pupil Processing Tools

This section will present the processing tools applied to the pupil data available in the eye-tracking file. This file corresponds to output 10 of the Chapter "Data Management" and the set of features obtained by these tools are the output 6 of this chapter (see diagram A).

To do the pupil analysis, the $[Time]$ and $[RightDiameterY]$ were accessed, as well as the current trial and step of the experiment.

As a pre-processing step, the pupil diameter was converted from pixels to centimetres. As stated in section 2.2.1, the pupil variation reaches a peak in less than 1 second and, therefore, the analysis was performed for each phase of the IGT: choice, anticipation and feedback.

The signal of the pupil diameter over time falls to zero and this is usually caused by blinking the eyes. Sometimes, longer periods of zeros are caused by eye-tracking disconnection and these areas were ignored to do a correct interpretation of results. In case the percentage of pupil diameter equal to zero is higher than 35%, the respective participant was discarded.

As presented in Table 5.7, the pupil analysis is based on five measurements: the blinking percentage, which is basically the percentage of time the pupil diameter is equal to zero, the average pupil diameter, the average of the pupil diameter variation and two measurements related to the peaks of the signal. When the pupil diameter increases more than 0.5 mm, a peak is detected. The number of peaks and the area of each peak were computed features. The area of peaks is informative about the intensity and duration of each pupil variation. The final set of features are analysed in terms of blocks in the IGT, raising a total of 306 features.

Table 5.7: Features extracted from the pupil diameter signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT and \$ the phase of the trial (c=choice; a=anticipation; f=feedback)). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
##_\$ <i>blink</i>	-	Blinking percentage	1
##_\$ <i>diameter</i>	mm	Average pupil diameter	1
##_\$ <i>diameter_var</i>	mm	Pupil diameter variation	1
##_\$ <i>nr_peaks</i>	-	Number of peaks	0
##_\$ <i>area_peaks</i>	mm.s	Area of peaks	1

5.5 Electrocardiogram

This section will present the processing tools applied to the Electrocardiogram (ECG) data in the biosignals file. This file corresponds to output 11 of the Chapter "Data Management" and the set of features obtained by these tools are the output 7 of this chapter (see diagram A).

The first pre-processing step was the conversion of the Analog-to-Digital Conversion (ADC) signal to mV. From this step until the detection of the RR peaks, the signal processing filters applied were based in the Pan Tompkins algorithm [183], which is implemented in *novainstrumentation*¹ library. The last pre-processing stage was the exclusion of outliers from the signal. RR peaks with an interval shorter than 0.4 or longer than 2 are replaced by the previous correct interval (frequencies between 30-150 Beats per Minute (BPM)). If more than 25% of the RR peaks were detected as outliers, the respective participant was discarded.

Given the strong bond between psychophysiological measures and the Heart Rate Variability (HRV) analysis, we extract a set of features from linear (statistical, geometrical and frequency domain) and non-linear domain.

In the statistical domain, the Heart Rate (HR) is directly calculated using the interval of time between RR peaks:

$$HR = \frac{60}{\Delta RR} \quad (5.2)$$

Using the difference between NN, the RMSSD estimate the short-term components of HRV and the SDNN estimate the overall HRV [155]. Their definitions are in Table 5.8.

The percentage of NN differences greater than 50 ms (pNN50) are associated with short term, high-frequency variations in HR and with the activation of the peripheral nervous system [155, 228].

The geometrical features are based on the conversion of NN intervals sequences into geometrical patterns. The HRV triangular index is the integral of the density distribution (the number of all NN intervals) divided by the maximum of the density distribution. Triangular Interpolation of the NN Intervals (TINN) is the baseline width of the histogram of the NN intervals, measured as a base of a triangle approximation. Stress index is also computed from the HRV histogram and measure of the level of activity prevalence of central mechanisms regulation above Autonomous Nervous System (ANS) [228]. The logarithmic index, ϕ , corresponds to the coefficient of the negative exponential curve $k.e^{-\phi t}$, which is the best approximation of the histogram of absolute differences between adjacent NN interval [155]. The scatter created by the plot of every RR interval against the prior interval is called the Poincaré plot. By fitting an ellipse to the plotted points, the standard deviation of instantaneous beat-to-beat variability (SD1) is given by ellipse's width and the long-term standard deviation of continuous NN intervals (SD2) is given

¹<https://github.com/hgamboa/novainstrumentation>

Table 5.8: Features extracted from the ECG signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
Statistical			
##_hr	bpm	Heart rate	1
##_rmssd	ms	Root Mean Square of Successive Period Differences	0
##_sdnn	ms	Standard Deviation (SD) of all NN intervals	0
##_nn50	–	Number of pairs of successive NN intervals that differ by more than 50 ms	0
##_pnn50	–	Proportion of NN50 divided by the total number of NN intervals	0
Geometrical			
##_triang_index	–	HRV Triangular index	0
##_tinn	ms	Triangular Interpolation of NN interval histogram	0
##_si	–	Stress index	0
##_φ	–	Logarithmic index	0
##_sd1	ms	SD of instantaneous beat-to-beat variability	0
##_sd2	ms	SD of continuous NN intervals	0
##_sd1/sd2	–	Ratio between short and long interval variation	0
Frequency domain			
##_vlf	ms ²	Power in Very Low Frequencies	0
##_lf	ms ²	Power in Low Frequencies	0
##_hf	ms ²	Power in High Frequencies	0
##_lf/hf	–	Ratio between low and high frequencies	0
##_total_power	ms ²	Total power	0
##_%vlf	–	Ratio between VLF power and total power	0
##_%lf	–	Ratio between LF power and total power	0
##_%hf	–	Ratio between HF power and total power	0
##_lf_nu	–	Low frequency in normalised units	0
##_hf_nu	–	High frequency in normalised units	0
##_vlf_max	ms ²	Maximum frequency on the VLF	0
##_lf_max	ms ²	Maximum frequency on the LF	0
##_hf_max	ms ²	Maximum frequency on the HF	0
Non linear			
##_dfa	–	Fractal scaling	0
##_fd	–	Fractal dimension	0
##_he	–	Hurst exponent	0
##_lle	–	Largest Lyapunov exponent	0
##_cd	–	Correlation Dimension	0
##_ap_en	–	Approximate entropy	0
##_samp_en	–	Sample entropy	0
##_auto-corr	–	Auto-correlation of the time-series	0

by the ellipse's length. The ratio between the two measures ($SD1/SD2$) quantifies the unpredictability of the RR time series, which is used to measure autonomic balance [228].

The frequency-domain features discriminate the sympathetic and parasympathetic systems. To perform the frequency analysis, a cubic spline interpolation with 4Hz of frequency is applied to the HRV signal to then estimate the Power Spectral Density (PSD). The distribution of power in certain frequencies ranges may vary in relation to changes in autonomic modulation. The Low Frequency (LF) band ($0.04 < f < 0.15$ Hz) is mediated by the vagal and sympathetic systems, while the High Frequency (HF) band ($0.15 < f < 0.4$ Hz) is mediated by the parasympathetic system. The ratio between LF and HF measures the predominance of the sympathetic or parasympathetic systems [155]. Very Low Frequency (VLF) band ($f < 0.04$ Hz) increases due to physical activity and stress. Total power is the sum of the energy of all bands [228].

The activation of each frequency band in relation to the total power is also calculated. To emphasise the balance between the sympathetic and parasympathetic systems, LF and HF are also measured in normalised units (nu), which represent the relative value of each power component in proportion to the total power minus the VLF component [155]. Finally, the frequency with higher amplitude was extracted for each frequency band.

Non-linear features reveal information related to non-linear mechanisms involved in cardiovascular regulation. Below, a brief description of each feature is provided based on the review of the non-linear analysis of HRV made by Camille (2015), where the features and its applicability are more detailed outlined [43].

The Detrended Fluctuation Analysis (DFA) of a signal quantifies fractal scaling properties of NN intervals. This means that for higher DFA values there is a long-term correlation between RR intervals, which are related to sympathetic modulation [43]. The Fractal Dimension (FD) is a measure of the spatial regularity of the signal. It evaluates the minimum number of units of the signal that is required to reproduce a pattern of the same spatial size. The Hurst Exponent (HE) measures the predictability of the time-series, evaluating long-term dependencies and the degree of these dependencies; Largest Lyapunov Exponent (LLE) is related to the effects of the initial conditions on the signal. In a periodic signal, this exponent is zero. Correlation Dimension (CD) measures the self-similarity of the signal in terms of the independent functional components it needs to be described. Approximate Entropy (ApEn) measures the unpredictability and complexity of fluctuations in time-series. Sample Entropy (SampEn) is similar to ApEn, but is more consistent and depends less on the sample size. It was also computed the auto-correlation of the signal, using a time lag of 5 heartbeats [135]. The final set of features are analysed in terms of blocks in the IGT, raising a total of 216 features.

5.6 Blood Volume Pulse

This section will present the processing tools applied to the Blood Volume Pulse (BVP) data in the biosignals file. This file corresponds to output 11 of the Chapter "Data Management" and the set of features obtained by these tools are the output 8 of this chapter (see diagram A).

After converting the BVP signal to mV, a Butterworth bandpass filter from 0.02 to 2.1 Hz was applied to remove frequencies not related to the BVP signal. Regarding these low frequencies, the signal can be down-sampled and so we reduced the frequency to 250 Hz.

Similar to ECG, heartbeat can be extracted from the BVP signal. To detect the pulses, i.e. the systolic peak, we implemented an adaptation of the algorithm presented by [165]. The algorithm basically employs a Slope Sum Function (SSF) to the BVP signal, which enhances the BVP pulses keeping its information in terms of time and amplitude of the peak. Then, in conformity with Zong et al. (2003) an adaptive threshold is used to determine the occurrence of peaks. This threshold is updated when a maximum is detected, according to its value. For each SSF pulse, the maximum value is searched in the interval of time in which the signal is higher than the threshold [281]. If there is a big decay of BVP amplitude in consecutive pulses, the current approach will lose this pulse. To prevent this loss, a back search routine is implemented and a lower threshold is set in cases where the time difference between successive peaks is bigger than 110% [165].

The last stage of BVP processing was the exclusion of outliers from the signal, which is based on the heartbeats frequency and, therefore, follows the same rules as ECG. BVP pulses with an interval shorter than 0.4s or longer than 2s are replaced by the previous correct interval. If more than 25% of the BVP pulses were detected as outliers, the respective participant was discarded.

The set of features extracted from the BVP signal are described in Table 5.9. Taking into account that the HRV analysis is performed in the ECG processing tools, we simply considered the inter-beat time as a feature in this context. With relation with sympathetic and parasympathetic systems, the amplitude of the BVP signal is regarded in the remaining extracted features. This computation is described in previous studies [81, 110, 191]. The final set of features are analysed in terms of blocks in the IGT, raising a total of 114 features.

5.7 Electrodermal Activity

This section will present the processing tools applied to the Electrodermal Activity (EDA) data in the biosignals file. This file corresponds to output 11 of the Chapter "Data Management" and the set of features obtained by these tools are the output 9 of this chapter (see diagram A).

After converting the EDA signal to μS , the signal was down-sampled to a sampling frequency of 100 Hz, given that the frequencies of interest are within the range 0 to 1 Hz.

Table 5.9: Features extracted from the BVP signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
##_ibi	s	Interval between heartbeats	1
##_bvp	–	Filtered BVP signal	1
##_bav	–	BVP peak-to-peak amplitude variation	1
##_bvp_ampl	–	Difference between the maximum and the minimum of the BVP signal	0
##_pulse_width	s	Time to reach half the maximum value of the BVP peak	1
##_1st_deriv	s^{-1}	Mean value of the first derivative of the BVP signal	0
##_2nd_deriv	s^{-2}	Mean value of the second derivative of the BVP signal	0

As introduced in Section 2.1.3, there is relevant information in the phasic and tonic components of the EDA signal. Although these are distinguishable by their frequencies, the Skin Conductance Response (SCR) will continue overlapped. To correctly extract features from the SCR structure, several authors developed mathematical algorithms to model the morphology of the EDA signal (e.g. [5, 15, 49, 103, 151]).

To easily and effectively extract features from the Skin Conductance (SC) signal, we adapted the model developed by Gamboa et al. (2008) [92]. This model is sensitive to shape variability of SCR and consider therefore individual differences in SCR [25, 26]. We increased its efficiency in terms of computational time and adapt the filtering pre-processing procedures according to our experimental conditions. In summary, this entailed, firstly, filtering the signal with a low-pass filter, using fourth-order Butterworth low-pass filter with a cut-off frequency of 1Hz [103], the original model used a band-pass filter, which we decided to adjust to a low-pass filter, according to our experimental results. Second, we detected SCR events by determining the first order SC derivative (SC') [92], which will give the time parameters t_1 and t_3 (see Figure 5.16).

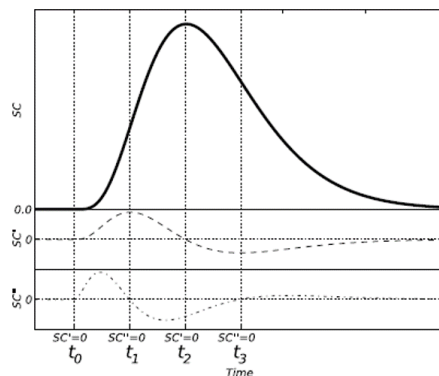


Figure 5.16: Skin conductance response morphology and respective first and second derivatives and time parameters, from [92].

To increase the model efficiency in terms of processing time, we used the first derivative of the signal instead of the second derivative, suggested by the original model.

An isolated SCR is mathematically formulated as the output of a linear system with transfer function $H(s)$ given by equation 5.3, to an impulsive-type input, representing the triggering stimulus of the SCR.

$$H(s) = \frac{\alpha}{(s+b)^n} \quad (5.3)$$

The identification of the model order, n , is based on matching the corresponding impulsive response $h(t)$, equation 5.4, given by the inverse Laplace transform of $H(s)$ with the observed morphological signal features. In this equation, $u(t)$ refers to the unitary step function, $k = n - 1$ and $a = \frac{\alpha}{k!}$.

$$h(t) = \mathcal{L}^{-1}\left(\frac{\alpha}{(s+b)^n}\right) = at^k e^{-bt} u(t) \quad (5.4)$$

The total EDA signal, f_{EDA} , is modelled by the sum of the SCR with a constant representing the Skin Conductance Level (SCL):

$$f_{EDA}(t) = h(t) + c \quad (5.5)$$

The b , a and t_0 parameters are computed using equations 5.6, 5.7 and 5.8. These are computed from the previously determined temporal marks t_1 and t_3 , and corresponding values of first order derivatives, f'_{t_1} and f'_{t_3} . This algorithm works for a series of overlapped SCR events, detecting small variations in the signal.

$$b = \frac{4}{t_3 - t_1} \quad (5.6)$$

$$a = b^3 \frac{f'_{t_1} - f'_{t_3}}{16e^{-2} + 432e^{-6}} \quad (5.7)$$

$$t_0 = \frac{3t_1 - t_3}{2} \quad (5.8)$$

At last, we computed, therefore, the SCL value by subtracting the detected SCR from the remaining signal.

Using this shape-sensitive EDA model, we were able to extract a set of morphological-based features (Table 5.10): SCL, SCR number, SCR number/minute, SCR maximum amplitude, SCR rise time, and SCR half-recovery time.

We computed also a new set of features which we refer to as SCR-loss correlation. Many previous studies identified a relation between the SCR and the losses in the IGT in good performance individuals [38, 44, 250]. This approach provided a means to specifically relate SCR shape variability to variability in the monetary losses.

Table 5.10: Features extracted from the EDA signal acquired in the IGT (## represents B1, B2, B3, B4, B5 or TT and \$ the phase of the trial (c=choice; a=anticipation; f=feedback)). Note is equal to 1 if this feature will be statistically analysed, resulting in 4 features (maximum, minimum, mean and standard deviation).

Name	Unit	Description	Note
##_scl	μS	Tonic level	1
##_scr	–	Number of detected peaks	0
##_\$_scr	–	Percentage of detected peaks for phase	0
##_scr_rate	–	Number of peaks per minute	1
##_scr_ampl	μS	Maximum amplitude of the peaks	1
##_scr_rise	s	Rise time of the peaks	1
##_scr_half_rec	s	Half recovery time of the peaks	1

The SCR-loss correlation was computed as follows. The monetary losses in the IGT trials were transformed into a time-series function. Considering that each loss (i.e., negative feedback) was an impulse response, to have a time-series function this input was convoluted with a Gaussian function [226] that was proportional to the loss (for a bigger loss corresponds to a wider Gaussian). Therefore, a Gaussian curve was considered to represent the monetary losses, in which the width of the Gaussian is proportional to the loss (see Equation 5.9). t_{loss} corresponds to the time the loss occurs on IGT, t to each instant of the IGT, w to the chosen time window in seconds and $lost$ to the amount of lost money.

$$monetary\ loss = e^{-\left(\frac{t-t_{loss}}{2 \times 0.001 \times w \times (\log(-lost))^2}\right)^2} \quad (5.9)$$

The Gaussian was added not only to form a waveform of the length of the entire EDA signal over the 100 trials, but also to each block of 20 trials of the IGT.

The monetary loss function was then correlated with parameters of the SCR:

- Number of SCR;
- Average of the total SCR signal;
- Mean of SCR amplitude;
- Sum of SCR amplitude;
- Mean of squared area - the SCR was approximated to a rectangular shape, with height equal to the SCR height and width equal to the difference between the t_1 and t_3 ;
- Sum of squared area - the SCR were calculated as the previous function;
- Mean of gaussian area - the SCR was approximated to a gaussian curve, with height proportional to the SCR height and width to the difference between the t_1 and t_3 ;

- Sum of gaussian area - the SCR were calculated as the previous function.

These features based on EDA were windowed and converted to a time-series function. Bearing in mind the individual differences of the EDA signal, a time window is defined for each individual, in a range of values between 1 and 30 s, according to its correlation with the Gaussian functions. In addition to this, while calculating the correlations between the EDA based functions and the loss time series, it was important to consider the arousal reaction to a stimulus, in this case to monetary loss, of each individual. Thus, different time shifts, with lags from -20 to 0 s, were tested.

In summary, the correlation between each EDA-based function and the loss wave is made for all time windows, between 1 and 30 s, and for all time shifts, between -20 and 0 s, and the highest correlation is recorded as well as the correspondent time window and time shift. All the correlations between the EDA functions and the loss wave were used as features. The mean value of the correlations for the different EDA-based functions was also used as a feature.

As an example, Figure 5.17 presents the highest correlation between the "Average of the total SCR signal" function and the loss wave in the first IGT block. There are two losses in the first block (red lines in the first plot), being the second loss bigger than the first (with bigger width). As a result, the second Gaussian added to the loss wave has also a larger width. Observing the loss time-series and the signal of EDA-related function, the correlation between the two resulted signals is apparently high. The correlation coefficient of these two waves is approximately 0.89, with a time window of 30 s and a time shift of -8 s.

The final set of features, considering the morphological features and the SCR-loss correlation features, made up a total of 189 features.

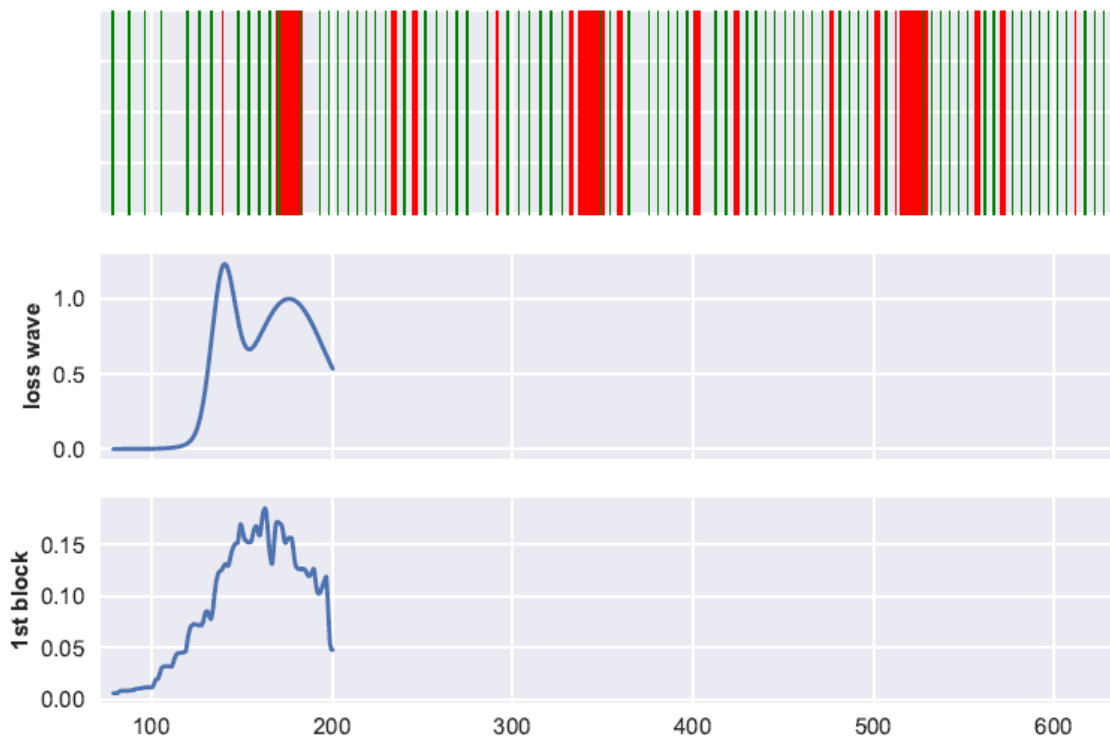


Figure 5.17: Example of EDA-based function and monetary loss function. The first plot presents in red the moments in which the subject loses money and in green the moments in which he wins, the lines' width are bigger for bigger losses (or wins). The second and third plots are the loss wave and the "Average of the total SCR signal" for the 1st block.

MODELLING PERSONALITY USING MACHINE LEARNING

This chapter includes the results of model personality prediction based on the different features described in Chapter 5. In diagram 6.1 is presented the main purpose of this chapter in this thesis: how data is combined to predict personality and what are the results of this combination. For this purpose, the results of Study 2 and Study 3 are individually included to analyse the relationship between personality and behaviour. First, in this chapter, all the steps included in the machine learning process are described. Second, the results of the personality questionnaires of Study 2 and 3 are presented. At last, the described machine learning approaches use the personality results as labels and the outputs of Chapter "Technical Tools" as features to generate predictive models of personality based on biosignals and Human-Computer Interaction (HCI) (see diagram A).

6.1 Machine learning algorithms

The ubiquitous computing led to a continuous recording of information. The large amount of data could be examined to find useful information associated with regularities or patterns. Data mining analyses and combines a large amount of information to find a strong bond between a smaller section of information, identifying which is the meaningful data for specific purposes. Machine learning algorithms provide the technical basis of data mining to find and classify patterns in data. These techniques are not only applied in research, but also in many areas of industry, such as financing services, marketing and sales or health care [275].

In case the learning approach has only the input data and no output to predict, it is called unsupervised learning. The goal is to organize and distribute the data to learn

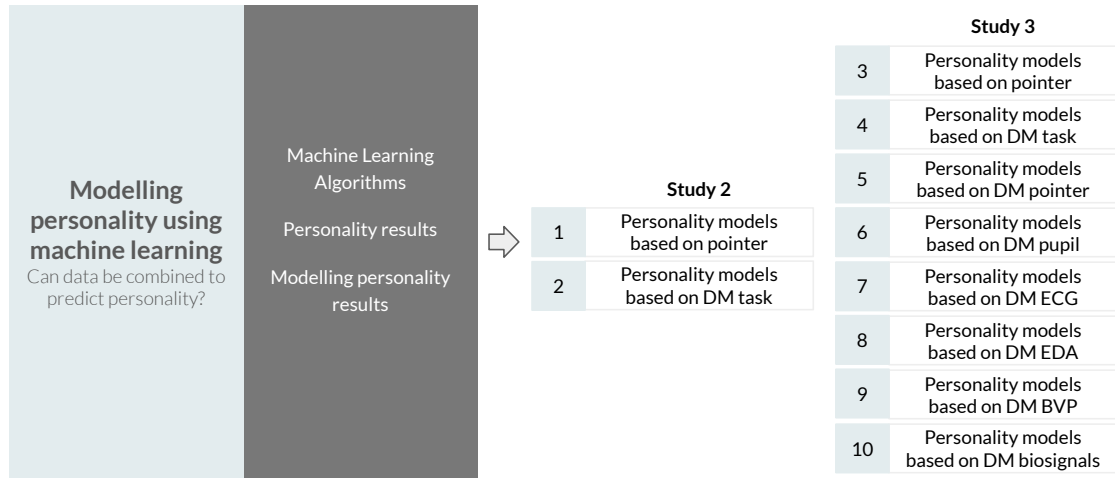


Figure 6.1: Details about what will be explained and what are the outputs of the Chapter "Modelling personality using machine learning" in the context of this thesis.

more about it. In supervised learning, in which the inputs are associated with output, may have two main goals: to predict or to infer the output [130]. In our specific case, the main aim is to accurately predict personality for future observations, however, the relationship between the inputs, i.e. features, and the output, i.e. personality, is also explored and, consequently, personality is also inferred.

Problems in machine learning can also be differentiated according to the output values. If the output is quantitative, that is described by numerical values, it is a regression problem. With a qualitative output, in which it is described by classes or categories, it is a classification problem. The methods used in machine learning are distinct for regression and classification problems [130]. This study has a continuous-value of personality as output and, therefore, we face a regression problem.

Considering our supervised learning and regression problem, there are many algorithms to combine features. What differs from the models is its flexibility and interpretability. More restrict models are easy to interpret, which is important if the aim is to infer the output. Non-linear models are more flexible, potentially leading to higher accuracy predictions, but the complexity of the algorithms make it more difficult to understand the association between the predictors and the prediction. These models are more suitable for improved predictions but less appropriate for inference [130].

In this study, the features extracted from the decision-making task interaction were individually modelled as predictors and the scores of the personality traits as the outcome.

Figure 6.2 summarizes the process of building the model in three main steps: (a) feature extraction, (b) model training and (c) model evaluation. The first step was the feature extraction, which was mainly based on the extraction of features described in

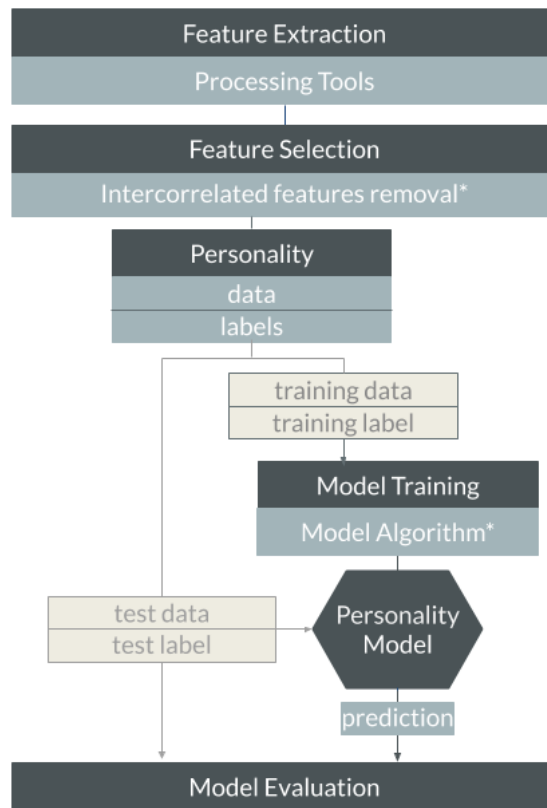


Figure 6.2: Steps in modelling of features in machine learning to identify the optimal subset of features that best predict the Big Five dimensions. Steps with * means it is run several times according to parameters variation.

Chapter 5. After extraction features, a feature selection is made by removing the inter-correlated features, applying different correlation features. The features extracted and the respective sample was distributed into training and test set. The training set was used to build the model using a model algorithm. Each Big Five dimension will experience the model training algorithm, having, in the end, a predictive model with distinct features importance. The models will be evaluated using the prediction of the test data and the respective label. All of these steps are described below.

6.1.1 Feature selection

Given that the extracted features may be highly correlated, which could mask interactions between features [130], a feature selection method based on Pearson correlation was executed [115, 126]. If the Pearson absolute correlation coefficient was superior to a threshold, the correspondent feature was left out. We worked with a threshold of 0.1, 0.3, 0.5, 0.7, 0.9, which correspond to very low, low, moderate, high and very high correlations,

to remove correlated features using different factors [172].

6.1.2 Model training

To do the model training, we decided to test several algorithms for each set of features and personality dimension. We used more restrict algorithms: Multiple Linear Regression (MLR), lasso regression and ridge regression; and more flexible algorithms: Random Forest (RF), Extra Tree (ET), Gradient Boosting (GB) and Support Vector Regression (SVR).

The model training procedure generated 35 models for personality dimension, considering five different correlation factors and seven modelling algorithms. It is worth to note that test data is not be included in training data [218]. For that, we applied train-test split cross-validation, in which 70% of our participants were subjected to model training and the remaining to model evaluation (for similar approaches see [16, 141, 150, 262]). To cover all range of the personality scale in both training and test set, a stratification process was applied and the sample is divided into low, medium and high according to the mean and standard deviation of the personality scale, to then split the train-test set [209].

Dealing with numerical features, in machine learning, it is important to have a normalized set of variables. We used a technique, called standardizing, that subtracts the statistical mean from each value and divide the result by the statistical standard deviation. The final set of values have a mean equal to zero and a standard deviation equal to one [274]. To keep the test set unseen by the training phase, the normalization is firstly performed to the training set of features, recording each mean and standard deviation. The normalization of the testing is based on the recorded mean and standard deviation of the training set.

6.1.2.1 Multiple Linear Regression

The MLR algorithm has as its target to minimize the residual sum of the squares of the differences between the observed and the predicted values for estimating the unknown intercept and slope parameters of a linear regression model. As presented in Equation 6.1, the predicted value (\hat{y}) is calculated by the linear combination of j predictors (x) with weights (β) [274]:

$$\hat{y} = \sum_{i=0}^k \beta_j x_j \quad (6.1)$$

Linear regression has the disadvantage of assuming linearity in the data, that does not regard possible non-linear dependencies in data [274]. In the case of high-dimensional, which means there are a large number of predictors in relation to the number of observations, a forward selection of features should be performed to avoid over-fitting and high-variance [273]. Specifically, a greedy forward selection algorithm (model begins with a set of null variables and add features one by one) was used to define the best combination of features [130]. While the features were recursively added, the model was

being built using the respective features. Based on methods of k-fold cross-validation the best number of features was selected. Rodriguez et al. (2010) [213] recommended the use of 5 or 10 folds if the aim is to measure the prediction error. We decided to use 5-fold to have more validation subjects [150]. This method randomly divides the data into exclusive k sets and, iteratively, uses each one as validation and the remaining population are utilized to train the model. With this method, every participant is used for training and validating the model and each participant is only validated once. To quantify the quality of the validation set predictions using different features, the Mean Squared Error (MSE) metric were measured:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2 \quad (6.2)$$

where n is the number of observations, y_i is the i th true response and $\hat{f}(x_i)$ is the prediction that the function gives for the i th observation. The goal is to minimize the MSE, which represent predict responses close to the true responses [130].

6.1.2.2 Ridge Regression

The ridge regression is an extension of linear regression, given that the minimization target is modified, to reduce the impact of irrelevant features in the model. A new term is summed to the residual sum of squares to generate a different set of coefficients. This term, $\lambda \sum_j \beta_j^2$, called shrinkage penalty, is small when the coefficients are close to zero. The λ controls the impact of this term: if it is zero, the ridge regression will be equal to the linear regression, if λ is high, the shrinkage penalty increases and the coefficients will approach zero. For each λ , a set of coefficients are computed, so choosing a good value is crucial. A cross-validation error is computed for a grid of λ to find the λ with smallest value [130]. We used 5-fold cross-validation to find λ , keeping the consistency of the feature selection in linear regression.

In comparison with linear regression, although the flexibility of the ridge regression decreases with the increase of λ , with a large number of features ridge regression decreases the variance, that is high with linear regression. This regression has the disadvantage of including all the predictors [130].

6.1.2.3 Lasso Regression

Similar to ridge regression, the lasso regression is an extension of the linear regression but in this algorithm the irrelevant features coefficients are set to zero. The term summed to the residual sum of squares is $\lambda \sum_j |\beta_j|$, which forces some coefficients to be zero with sufficiently large λ . This regression performs a feature selection, which is an advantage in terms of interpretability of the prediction but decreases the prediction accuracy [130]. We used a 5-fold cross-validation to find λ .

6.1.2.4 Ensemble Decision Trees

In case there is a highly non-linear and complex relationship between the features and the output, decision trees outperform classical approaches, i.e. linear regression. To build a decision tree, the predictor space is divided into J distinct and non-overlapping regions (R_1, R_2, \dots, R_J) , in which for every observation a prediction of the observed response is made to find the region that minimizes the residual sum of squares [130].

Briefly, the final structure of a decision tree is a flowchart, in which each internal node represents a "test" on an input variable, each branch represents the outcome of the test, each leaf node represents a label (i.e. a final decision) and the paths from the node to leaf represent rules. With this structure, it is easy to understand and explain the decision process behind the decision tree. However, decision trees are very sensitive to the trained data and small changes can significantly modify the results [130]. The aggregation of decision trees, like bagging or boosting, improves the prediction accuracy.

Random Forest is an ensemble of Decision Trees, which produces a more accurate and stable prediction merging multiple decision trees. To overcome the sensitivity of the decision trees, in RF each tree is trained on different sets of data through bagging, a method that randomly samples a data set with replacement. The features considered in each node are from a random subset of features to create an uncorrelated forest of trees whose prediction is more accurate than that of any individual tree. The subset of random features should be smaller than the set of features to avoid this problem. In case there are highly predictive features, these appear on the top of the tree and create similar trees [36, 130]. To tune the model, the subset of features used at each node was one-third of the total features, as recommends by [97]. The number of trees was set to 100 due to computational time cost.

The **Extra tree regression**, also known as extreme random forests, has only one main difference compared with RF regression, instead of computing the locally optimal feature combination, for each feature a random value is selected for the split. The algorithm randomizes both attribute and cut-point choice while splitting a tree node, but this randomization can be tuned according to the problem. In the extreme case, it builds randomized trees whose structures are independent of the output values of the learning sample. This model has good results in terms of accuracy, but the main strength is the computational efficiency [97]. In addition to the tuning parameters defined in RF, this method has one extra parameter: $nmin$, the minimum sample size for splitting a node that controls the degree of smoothing. It was set to $nmin = 5$, a value that seems to be robust in a broad range of typical conditions. The number of attributes randomly selected at each node controls the strength of the attribute randomization, which was again set to one-third of the features [97].

Gradient boosting, like RF, is an ensemble of decision trees. What distinguishes it from RF is the method used to grow the tree, instead of bagging it grows with boosting. In contrast to bagging, in which the data set is randomly sampled, in boosting the data set

is weighted and will take part of new sets more often. Consequently, each tree is trained using information from previously trained trees, so they are grown sequentially and from weak learners grow strong learners. GB identifies weak learners using gradients in the loss function, which is a measure indicating how good are the model's coefficients at fitting the data. Unlike RF, the number of trees in boosting should be restricted to avoid over-fitting. Furthermore, to control the learning rate, the shrinkage parameter should be defined considering the number of trees, given that to achieve a good performance with a small learning rate, many trees are needed [90, 130, 255, 275]. The number of trees was set to 100 and the learning rate to 0.1, a small value according to the number of trees.

6.1.2.5 Support Vector Regression

SVR, such as MLR, finds a function, called hyperplane, that approximates the training points to minimize the predictions' error within a certain threshold. While MLR finds a linear relationship between the predictors, support vector regression covers non-linear dependencies in data. Additionally, this algorithm tries to maximize the flatness of the regression function, that minimizes the risk of overfitting. The model uses a parameter that controls how closely the function will fit the training data, discarding deviations up to a boundary line. The support vectors are the data points within the boundary line. SVR is an advantageous method in case of high-dimensional data, but it is very time consuming and the resulting function is difficult to understand and interpret [130, 274]. To reduce the complexity of the model we used a linear kernel, no penalty will be associated with prediction points with a distance smaller than 0.1, which is the minimum step of our true values.

6.1.3 Model evaluation

As previously mentioned, the test set comprises 30% of the population and, because it should be a good representation of the whole sample, a stratification process was done. A stratification step evaluates different ranges of the personality scale instead of evaluating the whole population. This is relevant in this study to ensure that every range of the personality scale is evaluated and our conclusions are not only based on the range with higher population density. According to this, the test set was specific for each personality dimension.

The accuracy of the final models was given by a metric based on the MSE, which is a valid measure of model fit on an independent test set for high-dimensional data [130]. In the stratification process, we calculated the MSE for each range of the personality scale and, for the final model evaluation, we considered the mean of these values.

6.2 Personality baseline

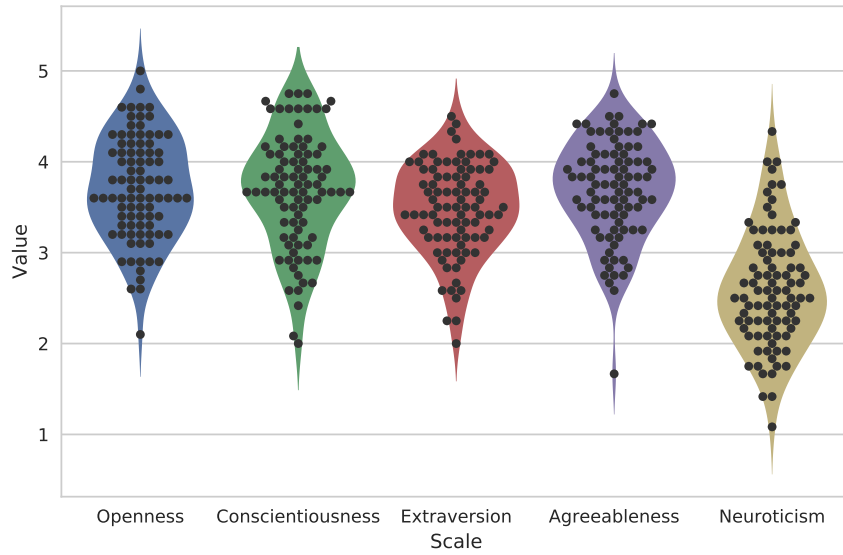
In our data from Study 2 and 3, recalling that the same questionnaire was carried out in both studies, the Cronbach's alphas [60], a metric that estimates the reliability of a psychometric test, were 0.75, 0.87, 0.77, 0.80 and 0.84 for the Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism scales, respectively. The internal consistency of the questionnaire is acceptable for values between 0.7 and 0.8 and good for values between 0.8 and 0.9.

In Table 6.1 is reported the resulting number of subjects that will be used to model personality based on the different inputs. As described in Chapter 5, some subjects were discarded due to lost data or artefacts in the signals, caused for example by the displacement of electrodes during the task. Even with a different number of samples, the mean, standard deviation, maximum and minimum of each personality scale do not change.

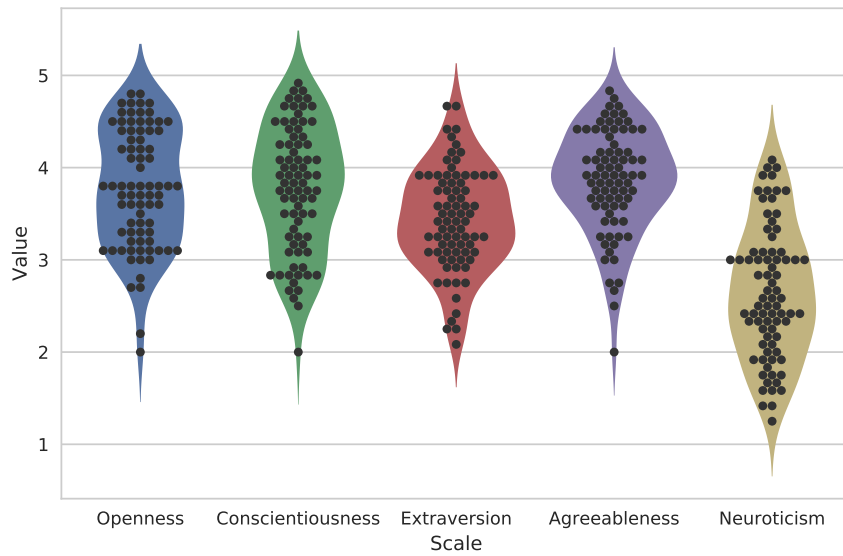
Table 6.1: Final number of subjects to build models.

Features	Number of Subjects	
	Study 2	Study 3
Mouse	78	76
DM Task	88	73
DM Mouse	-	79
Pupil	-	67
EKG	-	61
EDA	-	57
BVP	-	59
Biosignals	-	45

These results are reported in Table 6.2 and Figure in 6.3 represent the violin plots, a visual representation of estimated probability density function of the scales, of the results of the questionnaires for both studies' personality scales. The population distribution of most scales presents a shape similar to a Gaussian curve, meaning that there are few people in high and low scorers on these scales. In both studies, most people scored a value from 1 to 4 in the Neuroticism scale, so there are few high extremes on this scale. In the Openness, Conscientiousness and Agreeableness scales, the majority of the population scores values are above 3, which means that there are few low scorers. The majority of the population was classified with values between 3 and 4 in the Extraversion and Agreeableness scales. For scales Openness, Conscientiousness, Extraversion and Agreeableness, the range of 1-2 has none or very few subjects. Comparing both studies, the curves in 6.3 a) show higher standard deviation than curves in 6.3 b), which implies a more balanced distribution in personality scales in Study 3.



(a) Study 2



(b) Study 3

Figure 6.3: Violin plots of each personality scale distribution in Study 2 and 3.

Table 6.2: Personality results for Study 2 and 3.

Personality	Study 2	Study 3
Openness		
Mean	3.7	3.8
STD	0.6	0.6
Minimum	2.1	2.0
Maximum	5.0	4.8
Conscientiousness		
Mean	3.7	3.8
STD	0.6	0.7
Minimum	2.0	2.0
Maximum	4.8	4.9
Extraversion		
Mean	3.5	3.5
STD	0.5	0.5
Minimum	2.0	2.1
Maximum	4.5	4.7
Agreeableness		
Mean	3.7	3.9
STD	0.5	0.6
Minimum	1.7	2.0
Maximum	4.8	4.8
Neuroticism		
Mean	2.6	2.6
STD	0.6	0.7
Minimum	1.1	1.3
Maximum	4.3	4.1

6.3 Modelling personality results

This section presents the best results of the big five factors predictive models using the different sources of this study.

As mentioned before, for each set of data 35 models will be produced for each personality scale. However, we are interested in the model that is more accurate predicting personality. Therefore, for each scale of personality and each data set, the best model will be presented and described in a plot representation of the observed values (in the y-axis) versus the predicted values (in x-axis) as recommended by [196]. A dashed black line represents the ideal position of the points, where the predicted values are equal to the observed ones. Regarding the model evaluation, it was based on a stratified MSE, the plotted points are in different colours according to the range of the scale where they are located: lighter blue for low values and darker blue for high values in the personality

scale. This colour gradient will be helpful in a supplementary visualization that presents the histogram of the absolute errors with different colours by the range of the scale. The representation of the distribution of the predictive error will provide a quantification of what we see in the plot of observed vs predicted values. The two visualizations together support us in interpreting the results. First, with a visual inspection of how close are the predicted values to the observed values and then a quantitative analysis of the frequency of the absolute errors, for the different ranges considered to calculate the stratified MSE.

The details about the model itself will be presented on a table, in which each scale is associated to a model algorithm and the number of features from the application of the correlation factor, that are the two variables while building the models. For MLR, it is also presented the number of features that results from the forward selection. Then, the stratified MSE is presented as it is the criteria to select the best models. To examine the influence of each range of personality scale in the final stratified MSE, the MSE for the different values of personality is presented. Lastly, if there is a classification out of the scale, that is less than 1 or higher than 5, this point is considered equal to 1 or to 5, respectively. The number of outliers is reported in the table of results.

Taking into consideration the large amount and diversity of features provided to the models, the interpretation of each personality model is crucial to understand what features influence the final result. Since this analysis is unnecessary for models with low predicting accuracy, we decided to make the analysis on models with an error of less than 30% of the maximum mean error. The maximum mean error was calculated by Equation 6.3, in which o is the observed values and wp is the worst prediction.

$$\max(error) = \frac{\sum_{i=1}^5 |o_i - wp_i|}{5} = \frac{|1 - 5| + |2 - 4| + |3 - 5| + |4 - 2| + |5 - 1|}{5} = 3.2 \quad (6.3)$$

Therefore, models with an error inferior to $30\% \times 3.2 = 0.96$ will be considered. Given that the models are evaluated by the MSE, the error is squared: $0.96^2 = 0.92$. If there is any range with a MSE higher than 0.92, this model will not be further analysed.

At last, only the features with an importance that is higher than 30% of the importance of the best feature will be considered, i.e., if the best feature has an importance of 0.3, we only consider features with an importance that is higher than 0.1.

6.3.1 Model based on survey mouse features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 2 from 108 features to 85, 55, 42, 23 and 9 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively. In Study 3, the reduction was to 85, 59, 42, 23 and 6 features to 0.9, 0.7, 0.5, 0.3, 0.1 respectively. Only by observing this output, we can conclude that, while not very different, the final number of correlated features are not the same in both studies, which means

that the limited number of subjects in each study is not enough to generalize the results to a whole population.

Generally, by looking at Figure 6.4, predictions in Study 2 are closer to the observed values than in Study 3, as can be seen in the left side plots that represent the observed values over the predicted values of the best predictive models for each scale of personality. This could be a consequence of the attached biosignals sensors in Study 3, which is an extra stressor for the subjects. In a stress situation, noisy tremors in hands movements affect the mouse dynamics that consequently affect the personality predictive models.

Recalling that the MSE of 0.92 is the threshold value that defines what a good predictive model is, we can infer that the mouse features that modelled openness, conscientiousness and extraversion had good predictive results in the two studies carried out, but neuroticism was only well predicted in Study 2. Agreeableness did not achieve good results.

In terms of the model algorithm, more complex algorithms, especially ridge and SVR, have a better performance in predicting personality in Study 2 (see Table 6.3). Both algorithms build a linear function to model personality, so the relationship between the mouse features and personality are linear. This is not verified to openness in Study 3, that is better predicted by GB. Although MLR is the best algorithm to predict personality dimensions in both studies, the outcomes are not good enough to be considered a good predictive model.

Table 6.3: Details about the best predictive model based on the mouse movements in online surveys for each personality scale in Study 2 and Study 3. *CC* are the features resulted from the feature selection based on the correlation coefficient and *GFS* are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
Study 2								
O	Ridge	42	0.19	-	0.01	0.22	0.35	1
C	Ridge	85	0.46	-	0.42	0.40	0.55	2
E	SVR	85	0.29	-	0.23	0.53	0.13	3
A	MLR	55/14	0.56	-	0.20	0.53	0.96	1
N	Ridge	23	0.40	0.35	0.16	0.67	-	0
Study 3								
O	GB	6	0.50	-	0.26	0.36	0.89	0
C	Ridge	23	0.44	-	0.43	0.47	0.41	0
E	Ridge	42	0.39	-	0.90	0.16	0.19	0
A	MLR	23/4	1.38	4.00	0.99	0.07	0.44	0
N	MLR	23/4	0.64	0.99	0.25	0.59	1.96	0

Openness is well predicted in both studies, and it is the personality scale with the best result for Study 2. However, the MSE in Study 2 is lower than in Study 3 and, as confirmed

6.3. MODELLING PERSONALITY RESULTS

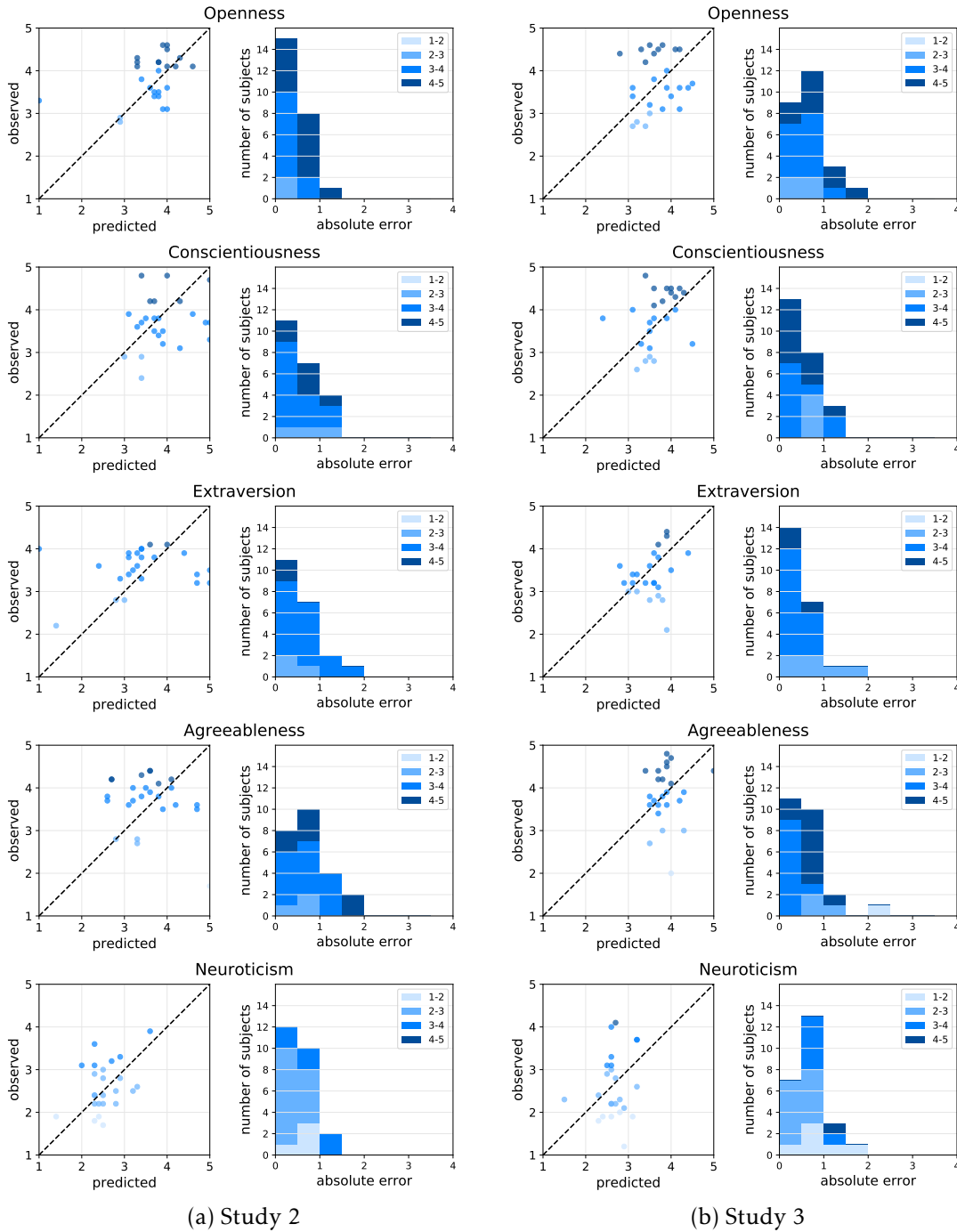


Figure 6.4: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 2 and 3 based on mouse movements features in online survey.

by Figure 6.4, the points are more disperse concerning the ideal line of prediction in Study 3. Furthermore, in both studies, high openness subjects (dark blue) are the worst results. It is still worthy to consider that there is one subject with a prediction out of the range (1 to 5) in Study 2, while in Study 3 all subjects were classified within the dimension.

The models were based on different algorithms (ridge and GB) and with a different set of features (42 and 6). Nevertheless, the MSE consistently increase with increasing openness level. The features with a higher importance in each model are presented in Table 6.4.

Table 6.4: Features with high importance for predicting openness with mouse features.

Study 2		Study 3	
Feature	Coefficient	Feature	Importance
jerk_mean	-0.08	#correc_within_item	0.12
answer_ratio_min	0.10	#items_zapped	0.15
t_item	-0.11	w_max	0.23
s_stroke_min	0.13	t_item_mean	0.23
#strokes	0.14	t_item_max	0.27
pause_bef_click_min	-0.15		
#correc_between_item	-0.15		
answer_ratio_std	-0.20		

In Study 2, the alpha obtained by cross-validation in ridge regression was 10, which reduces the coefficients of the fitting compared to linear regression. The three more important features are contextual and are negatively correlated with openness, which means that people high in openness do not vary the hovering time of the final answer in relation to the others along with the questionnaire, do not go back to previous questions to change the answer and have very long pauses before clicks. The number of strokes is high, but also its length. Additionally, they are very fast in answering the questions and the jerk, which is the variation of the acceleration, is low for high openness. Finally, in addition to the variation of hovering the final answer in relation to the others, the minimum of this ratio is also high. These are only 8 of the 42 features of the model.

In Study 3, with GB the importance of the features are returned in positive values and higher values correspond to higher importance. The set of features selected, in comparison with ridge regression in Study 2, is due to the different way of training the models. With higher importance to predict openness are features of the time of question and the angular velocity. The angular velocity is also relevant and two contextual features: the number scrolls and the number of correction made inside a question. In this model, 5 of the 6 features have high importance.

For conscientiousness, in Study 2 and Study 3, ridge regression with alpha equal to 10 gives the best result of all. Despite having a smaller MSE, in Study 2 there are two outliers and in Study 3 there is none. Visually, the number of subjects in the range of 2-3 for conscientiousness is similar in both cases, and its MSE is also similar. For the range

of 3-4, Study 2 has more subjects and achieved better accuracy, but in Study 3 if we look at the observed vs predicted plot (Figure 6.4a) it is possible to conclude that most of the points are close to the ideal line and there are three points more away, which is confirmed by the histogram of the absolute error. In Study 3 there are more subjects in 4 to 5 and the prediction MSE is lower, which is expected given that the MSE of Study 2 is only based on 4 points that most are away from the ideal line and a fifth point was classified out of range.

Regarding the importance of the features to the models, it is expected that with the same model algorithm, also the features should be similar. Exploring the best features reported in Table 6.5, disregarding the different amount of features required, these are still very distinct. Interestingly, the only two features equal in both studies have similar coefficients. The minimum length of the strokes are consistently small for high conscientiousness and the minimum time for a click is high for high conscientiousness subjects. The large number of different features led us to conclude that the sample of subjects in each study is not enough to create a generalized model and more subjects are needed to find a consistent set of features that describe conscientiousness.

Extraversion is the best predictive scale for Study 3 and the second-best for Study 2, but it still has a lower MSE in Study 2. Nevertheless, in Study 2 there are 3 outliers, which means that 4% of the population are classified out of range. In both cases, there are no low extraverted subjects (range of 1-2). Even Study 2 has fewer points in extremes (2-3 and 4-5) than Study 3, these are better predicted. The range of 3-4 has better results in Study 3, in which all subjects are predicted with a MSE lower than 1, while in Study 2, in addition to the 3 outliers in this range, there are three subjects with a MSE higher than 1.

In Table 6.6 are presented the features with higher importance to the models. The two models have different algorithms: SVR and ridge ($\alpha=10$) for Study 2 and 3, respectively. Considering not only the different algorithms but also that each one predicts better different ranges of extraversion, 27% of the features are selected in both studies, but only 18% have similar correlations. The maximum curvature of the movements are higher for high extraverted, but the maximum of abandon times, the number of items scrolled and the inter-item interval minimum is small for high extraverted subjects. The number of corrections made between items and the minimum time of click decrease in one model and increase in the other for high values of extraversion.

Following previous studies [35, 77, 217] that conclude that extraverts click with more frequency and move the mouse faster than introverts, the results of Study 2 reported small time of clicks, fast inter-item interval, small inter-item interval, more velocity and less time paused for high extraversion. On the other hand, Study 3 reported features that do not support previous findings, like the longer time of clicks and time of pauses for high extraverts, and features that support previous studies, like fast velocity and short inter-item interval for extraverts.

As observed in Figure 6.4, agreeableness is not well predicted in both studies and, because the associated MSE is higher than the threshold established (see Table 6.3), the

Table 6.5: Features with high importance for predicting conscientiousness with mouse features.

Study 2		Study 3	
Feature	Coefficient	Feature	Coefficient
#overviews	0.06	s_stroke_min	-0.11
t_pauses_mean	0.07	w_max	-0.12
s_stroke_min	-0.07	t_item_mean	0.13
#strokes	-0.07	t_click_min	0.14
t_pauses_min	-0.07	answer_ratio_std	-0.16
inter-item_interval_min	-0.08	θ _mean	0.17
#ans_hovered_min	-0.08	t_item_max	-0.23
s_stroke_mean	0.08		
straightness_max	-0.08		
#uncertainty	-0.08		
<-turns	-0.08		
pause_bef_click_min	-0.09		
v_y_max	0.09		
distance_answer_min	0.10		
t_click_min	0.10		
t_bef_click_min	0.10		
#hover_text	-0.10		
distance_answer_max	0.10		
#correc_between_item	0.11		
t_abandon_std	-0.11		
t_bef_click_max	-0.12		
v_x_max	-0.13		
inter_item_interval_std	0.14		
#ans_hovered_max	-0.16		
#ans_hovered_mean	0.16		

features are not explored. In Study 2, in contrast to the few points in the range of 2-3 that have a small absolute error, the points higher than 3 are more disperse and with a higher error. In Study 3, most of the points of the range of 3-4 have an absolute error inferior to 0.5, but for higher values the error increases and for lower values the error is even worse.

Similar to agreeableness, also neuroticism can not be well predicted in Study 3, most of the subjects are predicted between 2.1 and 3.1 on a scale that ranges from 1.1 to 4.1. In Study 2 subjects below 3 in the scale of neuroticism are predicted with an absolute error inferior to 1, but higher values have a MSE of 0.67. In this scale, no subjects had neuroticism higher than 4.

The ridge regression with alpha equal to 10 was the algorithm that better adjusted mouse features to neuroticism and the more relevant features are in Table 6.7. According to this model, the time of click has a high impact in predicting neuroticism, with a direct correlation with its minimum and an inverse correlation with its maximum. Smaller curvatures while moving the mouse fewer corrections inside an item are also related with

Table 6.6: Features with high importance for predicting extraversion with mouse features.

Study 2		Study 3	
Feature	Coefficient	Feature	Coefficient
#zapp	-0.14	straightness_min	0.05
distance_answer_mean	-0.16	t_click_min	0.05
t_accum_max	0.16	v_y_min	0.06
c_mean	0.16	#skips	0.06
c_max	0.16	θ _min	-0.06
t_click_min	-0.16	inter_item_interval_min	-0.06
#overviews	-0.17	#zapp	-0.06
t_item_std	0.17	c_max	0.06
#uncertainty	-0.17	t_pauses_min	0.06
w_std	-0.18	v_t_max	0.07
pause_bef_click_min	0.18	s_stroke_min	-0.07
inter_item_interval_min	-0.18	straightness_std	-0.07
\bar{s}	0.19	a_mean	-0.08
#revisits	0.21	#correc_between_item	0.08
distance_answer_min	0.21	ans_hovered_std	0.08
#correc_between_item	-0.24	v_x_min	-0.09
t_abandons_max	-0.25	v_t_min	0.09
v_t_mean	-0.27	#hover_text	-0.12
t_pauses_max	-0.27	#abandon	0.12
θ _mean	0.27	<-turn	-0.13
t_bef_click_max	0.28	#ans_hovered_mean	0.14
v_y_mean	-0.29	t_abandon_max	-0.17
jitter_min	0.29		
pause_bef_click_max	0.31		
jitter_max	-0.35		
pause_bef_click_mean	-0.35		
w_max	-0.37		

high neuroticism. Furthermore, a non-linear order while answering the questions, the minimum angles of movement and the length of strokes are more related to neurotics.

6.3.2 Model based on decision-making task features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 2 from 132 features to 103, 54, 34, 15 and 7 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively. In Study 3, the reduction was to 104, 59, 28, 14 and 6 features to 0.9, 0.7, 0.5, 0.3, 0.1 respectively. Only by looking at this output, we can conclude that, while not very different, the final number of correlated features are not the same in both studies, which means that the limited number in each study is not enough to generalize the results to a whole population.

Table 6.7: Features with high importance for predicting neuroticism with mouse features.

Study 2	
Feature	Coefficient
s_stroke_min	0.09
θ _min	0.09
#skips	0.11
c_max	-0.11
t_click_max	-0.11
#correc_within_item	-0.13
t_click_min	0.21

Generally looking at Figure 6.5, the predictive models are worse compared to the ones based on the mouse features, previously presented. Some scales, like neuroticism, is closer to the ideal line in Study 2 than in Study 3, while other scales, like agreeableness, is better predicted in Study 3.

Recalling that the MSE of 0.92 is the threshold defined to consider a good predictive model, based on the IOWA Gambling Task (IGT) features, openness is well predicted in the two studies carried out, but extraversion and neuroticism were only well predicted in Study 2, and agreeableness had good results in Study 3. Conscientiousness did not achieve acceptable results in this case. In terms of the model algorithm, more complex algorithms, especially GB and SVR, have better performance in predicting personality in Study 2 and 3 (see Table 6.8). In Study 2, a simple MLR achieved good results to predict extraversion.

Table 6.8: Details about the best predictive model based on the IGT features for each personality scale in Study 2 and Study 3. CC are the features resulted from the feature selection based on the correlation coefficient and GFS are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
Study 2								
O	GB	15	0.43	-	0.67	0.25	0.37	0
C	SVR	7	0.57	-	0.52	0.14	1.06	0
E	MLR	54/17	0.36	0.25	0.54	0.35	0.30	1
A	SVR	34	0.76	1.69	0.39	0.19	0.77	0
N	GB	7	0.43	0.47	0.24	0.58	-	0
Study 3								
O	GB	6	0.51	-	0.63	0.30	0.60	0
C	MLR	104/25	0.79	0.25	1.46	0.46	1.00	4
E	MLR	28/15	0.59	-	1.07	0.32	0.36	0
A	SVR	104	0.43	-	0.01	0.46	0.83	1
N	GB	6	0.72	0.85	0.23	1.08	-	0

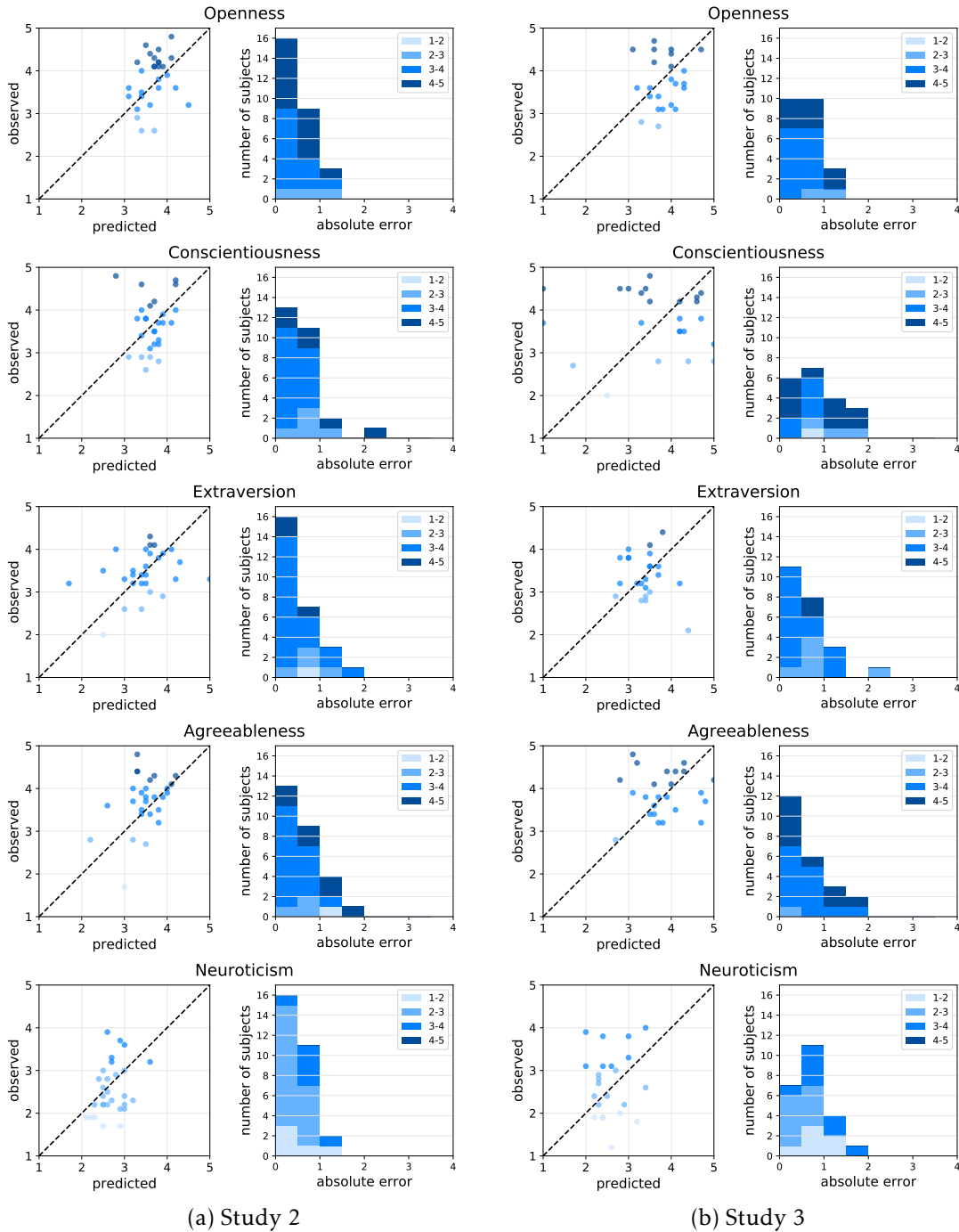


Figure 6.5: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 2 and 3 based on the IGT features.

Openness is, as has happened with mouse features, a scale accurately classified in both studies using IGT features. The MSE is bigger in Study 3 and, by looking at Figure 6.5, we conclude that this is caused by predictions in high openness, which has a higher error in Study 3. Again, individuals ranging of 1-2 in openness can not be predicted with this model considering that we do not have subjects to train and test these values. It is also worth noting that, in both studies, there are no outliers, thus the reported MSE contemplated the whole sample of subjects.

Concerning the models themselves, despite having a different number of features, the algorithm was the same: GB. Consequently, the set of features should be similar in both studies to prove that the models can be extended to further predictions. In Table 6.9 are presented the most important features in Study 2 and Study 3.

Table 6.9: Features with high importance for predicting openness with IGT features.

Study 2		Study 3	
Feature	Coefficient	Feature	Coefficient
B1_highest_reward	0.04	B2_highest_reward	0.09
TT_penalty	0.05	B5_highest_reward	0.11
TT_RT_min	0.05	TT_penalty	0.16
B4_RT_reward_mean	0.06	TT_reward	0.21
TT_reward	0.07	TT_RT_max	0.21
B4_penalty	0.07	TT_RT_penalty_mean	0.23
TT_deck1	0.08		
B2_RT_reward_min	0.08		
B3_RT_max	0.08		
B3_penalty	0.08		
TT_RT_max	0.09		
B1_total_money	0.10		
TT_RT_reward_mean	0.11		

To interpret models based on GB algorithm, the importance of the features are given by a positive value that is high with higher importance, thus we can describe which features have an impact in modelling openness but no conclusion can be made in terms of how the features influence the model. In Study 2, the feature that is more related to openness is the mean of the reaction times after reward for the total game and the total money, while in Study 3 the most important feature regards the reaction times after penalty instead of rewards. Only three features are common to both studies: *TT_penalty*, *TT_reward* and *TT_RT_max*, which means that the sum of all the penalties and rewards, and the maximum reaction times at the end of the game, characterize openness individuals. Although the feature that represent performance is not included in the most important set of features, the rewards and penalties can be related with decision-making skills and, therefore, confirm that high openness is ineffective in decision-making tasks, as stated by [277]. The feature *TT_deck1*, a "bad" deck, can also be related to the tendency of high openness individuals to take more risks [144, 176], that causes a decrease in rewards and

increase in penalties [270]. The majority of the important features are extracted from the total time of the game, 46% in Study 2 and 66% in Study 3, and these are also the common features in both studies. However, features from each block of the game are also presented as relevant to modelling openness.

To predict conscientiousness, the model-based only on the IGT features in Study 2 has an absolute error inferior to 1 in the range of 3-4 and the points are close to the ideal line, as observed in Figure 6.5. However, the errors for the other scales are higher and because the MSE for range 4-5 is superior to 0.92, the features are not explored for this scale and study. In Study 3, the predictive values are very dispersed, there are 4 subjects classified out of the admitted range and, because the ranges 2-3 and 4-5 are above the maximum error threshold, the model of conscientiousness for Study 3 is also not explored.

For extraversion, it is possible to observe in Figure 6.5 that more introverted subjects are better predicted in Study 2 than they are in Study 3. In the range of 3-4 Study 3 performs better than Study 2, but analysing the histograms of errors, even with some points with higher error in Study 2 and more dispersed in the plot of observed vs predicted, there are many points with an error less than 0.5 (13 individuals). The few extraverted subjects (range 4-5) were classified in both studies with an absolute error less than 1.

With a MSE higher than 0.92 in the range of 2-3 in Study 3, the importance of the features are only explored in the extraversion model in Study 2.

The model algorithm to predict extraversion in Study 2 is the MLR thus the features can be analysed by its coefficients. In this model, the features selected are more from the blocks, instead of related to the total time of the game (see Table 6.10). The results show that 35% of the features are from block 1, which is the part of the game with higher ambiguity and, therefore, when the personality is more expressed.

Table 6.10: Features with high importance for predicting extraversion with IGT features.

Study 2	
Feature	Coefficient
B3_deck2	0.11
B2_highest_reward	0.12
B5_inefficiency	-0.13
B2_deck1	-0.13
B2_RT_penalty_min	-0.14
B3_RT_max	-0.14
B1_total_money	0.18
B3_RT_penalty_max	0.19
TT_RT_min	0.20
B1_RT_reward_mean	-0.21
B1_RT_min	-0.24
B5_penalty	-0.25
B1_RT_reward_min	0.29
B1_RT_max	0.34

Interpreting in more detail the features, in the very beginning of the task higher extraversion is associated with faster reaction time in some trials, and very high reaction time in others. After a reward, the mean reaction time is short and at the end of the first block, high extraverted subjects have more money. In block 2, after penalties, the reaction time is shorter, the individuals select less deck 1 ("bad" deck) which could mean they start to learn the strategy of the game. It is also in block 2 that they have higher rewards. In block 3, the maximum reaction time is shorter and deck 2 is more selected ("good" decks) which confirms the conclusions in block 2. Accordingly, in the last block, the high extraverted subjects are more effective and the sum of penalties is lower. Based on the same reasoning, we conclude that individuals high in extraversion are good performers of the IGT, however, this is only verified in Study 2.

For the dimension of agreeableness, although the MSE of levels of agreeableness higher than 3 are well predicted in Study 2, the MSE of 1.69 for the range of 2-3 exclude this model for further analysis. In Study 3, there are some points away from the ideal line, but the majority is close to the observed values. As observed in Figure 6.5, there are two points between 3 and 4 and three points between 4 and 5 with absolute error higher than 1, the remaining points are predicted with less error.

The model algorithm, SVR is supported by 104 features, so it is more difficult to interpret the relationship between features and agreeableness. The features with higher importance are presented in Table 6.11 and, in this case, the number of features from blocks is higher than from the total game. There are 10, 11, 9, 14 and 11 from blocks 1, 2, 3, 4 and 5, respectively, and only 3 features from the total game. No consistency is found to performance or decks selection, high agreeableness subjects are more efficient in block 2 and in block 3, 4 and 5 this performance reduces but keeps stable. The selection of "good" and "bad" decks have a pattern over the blocks, which suggests that no strategy is related to the scale of agreeableness.

Finally, neuroticism is the personality trait that more authors found to be related with IGT. By looking at the plot of the observed versus predicted values, the predictions made in Study 3 are very dispersed, especially in the ranges of 1-2 and of 3-4, which has a MSE of 1.08. In Study 2 neuroticism is also predicted with some disperse point in high values, but lower values (below 3) are closer to the ideal line. Most of the predictions have an absolute error inferior to 1, however, in this scale, there are no subjects with more than 4, so no conclusions can be made to the range of 4-5.

Considering the MSE for neuroticism in Table 6.8, the features are only explored for the model of Study 2, which are presented in Table 6.12. The model algorithm is GB, so only the features importance are reported and no conclusions can be made on its relation with the personality scale. No feature is reported for blocks 1 and 5 and 50% of the features are extracted from the total game. Probably, performance is related to neuroticism, given that the total sum of penalties and rewards are regarded. The more important features are not related to performance, but with reaction times, after rewards in blocks 2 and 4 and for the maximum reaction time of the entire game.

Table 6.11: Features with high importance for predicting agreeableness with IGT features.

Study 3			
Feature	Coefficient	Feature	Coefficient
B3_inefficiency	-0.06	B4_deck3	-0.10
B5_RT_penalty_mean	-0.06	B2_reward	0.10
B4_deck1	0.06	TT_RT_min	-0.10
B5_inefficiency	-0.06	B3_RT_reward_min	-0.11
TT_penalty	-0.07	B1_deck4	-0.11
B2_highest_reward	0.07	B2_RT_max	0.11
B4_reward	-0.07	B4_highest_reward	-0.11
B3_RT_penalty_mean	-0.07	B5_penalty	-0.11
B4_RT_max	0.07	B2_deck3	0.11
B4_deck2	-0.07	B5_deck3	0.12
B4_highest_penalty	0.07	B2_penalty	0.12
B2_deck4	-0.07	B4_deck4	0.12
B4_RT_penalty_mean	0.07	B5_RT_penalty_max	0.13
B2_deck2	-0.07	B2_inefficiency	-0.13
B3_highest_penalty	-0.08	B4_RT_min	0.14
B1_RT_penalty_max	-0.08	TT_RT_penalty_mean	-0.14
B1_highest_penalty	-0.08	B1_total_money	-0.14
B1_RT_penalty_mean	-0.08	B1_highest_reward	0.14
B2_RT_penalty_mean	0.08	B3_deck4	-0.14
B4_inefficiency	-0.08	B3_RT_penalty_min	-0.15
B3_RT_max	0.08	B4_RT_mean	-0.15
B4_RT_reward_min	-0.09	B5_RT_max	-0.15
B1_deck2	0.09	B5_deck1	-0.16
B2_RT_penalty_max	-0.09	B5_RT_penalty_min	0.16
B5_highest_reward	-0.09	B3_deck2	0.17
B1_RT_min	0.09	B3_RT_reward_mean	-0.17
B5_RT_reward_min	0.09	B1_RT_max	-0.19
B4_RT_reward_mean	0.09	B2_RT_reward_mean	0.19
B5_RT_mean	0.10	B1_RT_reward_mean	-0.20

Table 6.12: Features with high importance for predicting neuroticism with IGT features.

Study 2	
Feature	Coefficient
B2_highest_reward	0.08
TT_penalty	0.09
TT_reward	0.15
B3_RT_reward_mean	0.18
TT_RT_max	0.19
B4_RT_reward_mean	0.25

6.3.3 Model based on decision-making task mouse features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 3 from 468 features to 326, 177, 89, 42 and 10 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively. From now on, our conclusions are only based on Study 3. The comparison between two models based on two populations cannot be done.

The plots of the observed versus the predicted values, presented in Figure 6.6, demonstrate that the traits of extraversion, agreeableness and neuroticism are not well predicted by the mouse features in the IGT, in which the points show no tendency to be distributed around the ideal line of prediction. This conclusion is confirmed by the MSE presented in Table 6.13, which is very high for the range 2-3 of extraversion and agreeableness. The model of neuroticism has no outliers but still has a high MSE in the range of 3-4.

For conscientiousness, more points are close to the ideal prediction line, particularly for values below 4. However, in this range, there are two outliers. For conscientiousness higher than 4, most of the points are predicted between 2.8 and 3.7, which results in a MSE of 0.92, the limit for further analysis.

At last, the plot for openness suggests that it is the best predictive model using mouse features of the IGT, with all points distributed around the ideal line of prediction. However, half of the points between 2 and 3 have an absolute error higher than 1, as observed in the histogram of the absolute errors, resulting in a MSE of 0.94.

Table 6.13: Details about the best predictive model based on the mouse movements features in the IGT for each personality scale in Study 3. *CC* are the features resulted from the feature selection based on the correlation coefficient and *GFS* are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	Ridge	89	0.51	-	0.94	0.33	0.26	0
C	MLR	89/32	0.52	-	0.23	0.41	0.92	2
E	GB	10	0.87	-	1.27	0.43	0.90	0
A	Ridge	42	0.83	-	1.82	0.23	0.44	1
N	SVR	10	0.55	0.54	0.18	0.93	-	0

None of the personality models based on the mouse interaction in the IGT achieved a performance good enough for further analysis. Although for the best of our knowledge, no previous studies analysed mouse interaction in the IGT, we were expecting better results bearing in mind psychophysiological findings were based on the pointer movements in cognitive tasks (e.g. [92, 195, 225]).

6.3. MODELLING PERSONALITY RESULTS

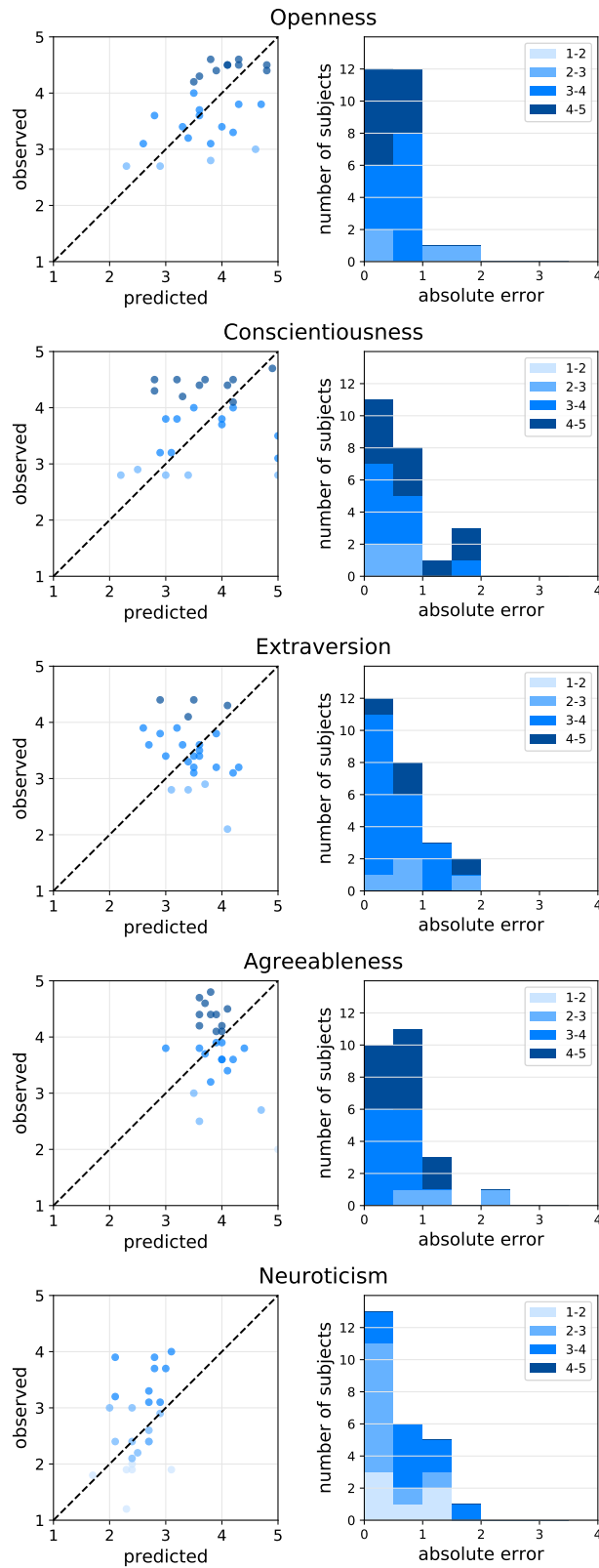


Figure 6.6: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the mouse movements features in the IGT.

6.3.4 Model based on pupil features

The result of the feature selection was a reduction in the sample of features of Study 3 from 306 features to 168, 59, 22, 10 and 4 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively, to remove the correlated features in Study 3.

The plots of the observed versus the predicted values, presented in Figure 6.7, clearly show that the traits of conscientiousness, agreeableness and neuroticism are not well predicted by the pupil features in the IGT, in which the points are completely dispersed around the ideal line. This conclusion is confirmed by the MSE presented in Table 6.14, in which these scales have at least one range with MSE higher than 0.92, the defined threshold.

The algorithms that had the best results are the MLR for openness and GB for extraversion, both with 22 features, but with a forward selection MLR ended up with 3 features.

Table 6.14: Details about the best predictive model based on the pupil features during the IGT for each personality scale in Study 3. *CC* are the features resulted from the feature selection based on the correlation coefficient and *GFS* are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	MLR	22/3	0.35	-	0.04	0.43	0.58	0
C	MLR	22/4	0.87	1.95	0.15	1.17	0.20	12
E	GB	22	0.47	-	0.46	0.18	0.76	0
A	GB	4	0.67	-	0.97	0.25	0.80	0
N	MLR	59/32	0.69	0.98	0.29	0.80	-	0

Openness is the scale that was best predicted using the pupil features, ending up with a MSE of 0.35. This scale has a very restrict sample in half of the scale (from 1 to 3), but the one existing subject is really close to the ideal line, with a MSE close to 0. The predictions for individuals with openness higher than 3 are largely well classified, but two of the predictions in each range (3-4 and 4-5) have an absolute error higher than 1.

The three features presented in Table 6.15 are the most important and the only ones used in the MLR algorithm to predict openness. The most important feature is the minimum area of the peaks in the signal in the choice phase, for the whole game, which means that for people high in openness the minimum pupil variation duration and intensity is higher than in low openness subjects. Due to latency time, these peaks could be related to the feedback phase, and therefore with learned uncertainty, as stated by [202]. At the last block of the game, the minimum diameter of the pupil is lower for high openness subjects in choice phase, showing no surprise or effect of learning at the end of the game [145]. The last regarded feature is associated to the second part of the game, in which the variation of the pupil diameter increases during the feedback phase for high openness,

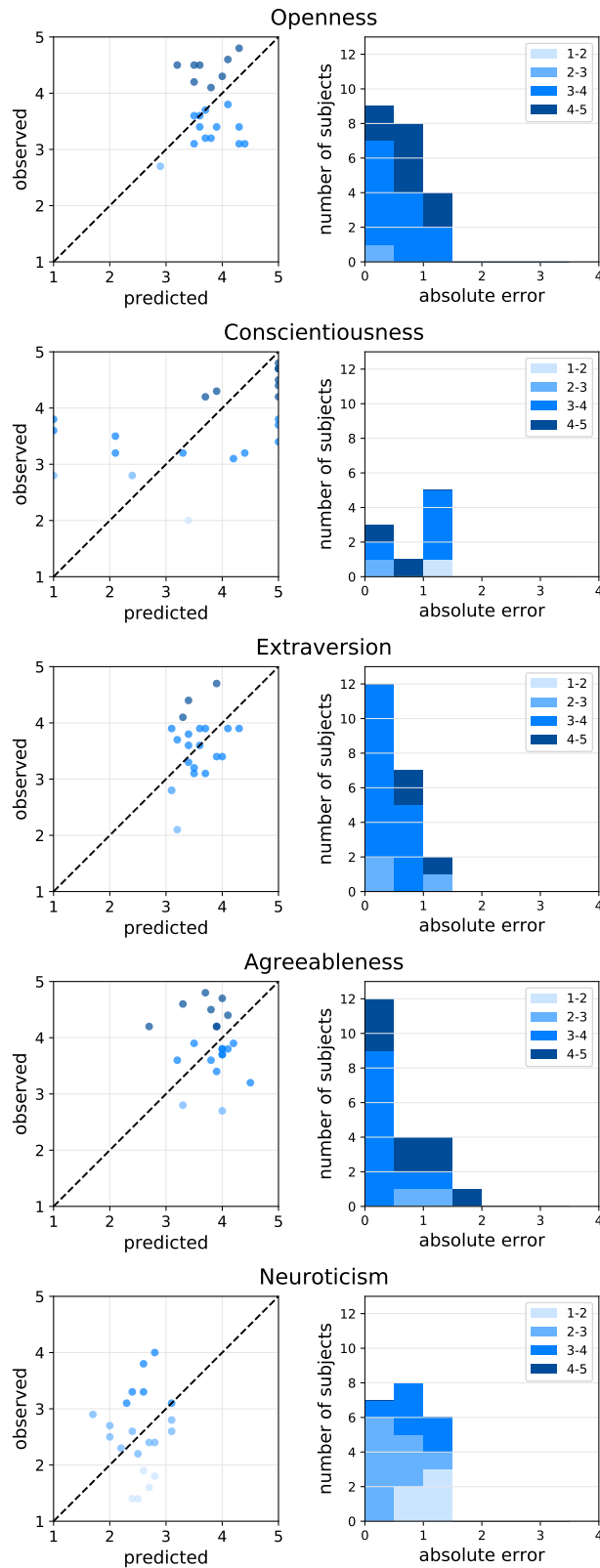


Figure 6.7: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the pupil features during the IGT.

which according to [202] reveals less uncertainty than low openness subjects.

Table 6.15: Features with high importance for predicting openness with pupil features.

Study 3	
Feature	Coefficient
B2_f_diameter_var_mean	0.15
B5_c_diameter_min	-0.28
TT_c_area_peaks_min	0.34

No relation can be established between pupil features and conscientiousness. Even without the 12 subjects classified out of the range, the range of 1-2 and 3-4 still has a big error.

Extraversion is predicted with 22 features, as it is openness, but with a more complex algorithm GB. Even with most predictions close to the ideal line, extraversion is predicted with more dispersion than openness, as seen in Figure 6.7. Every subject is classified within the range of 1-5, but there are no observed values in the first range (1-2) and only three subjects are in each of the extreme range. Of these three values, one is classified with an error higher than 1 for the ranges 2-3 and 4-5, thus this predictive model is restricted to the range of 3-4 in extraversion.

In contrast to openness model, the extraversion model using GB has much more relevant features, as presented in Table 6.16. Extraverts are more differentiated than introverts through all game, given that more than 50% of the features are from the total game. Every contemplated feature showed some relevance in this model, as well as the phases of the game, that although 50% are features calculated in choice phase, the remaining ones are also required more than once.

The model that predicts agreeableness is again tested in very few subjects in the lower half of the scale. The best results using GB algorithm and only 4 features can predict well some point from the 3 available ranges, but there are still many points away from the ideal line, as seen in Figure 6.7. Given the MSE of 0.97 in the range of 2-3, the features used in this model are not explored.

For neuroticism, the best predictive model relies on more features but in a simple algorithm (MLR). As opposed to agreeableness, the evaluation of this model has no high neurotics to test. Observing Figure 6.7, it is possible to notice that observed values from 1.4 to 4 are mostly predicted between 2 and 3. With a MSE higher than 0.92 in the lowest range of neuroticism, the features used in this model are not explored.

6.3.5 Model based on electrocardiogram features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 3 from 215 features to 152, 82, 38, 15 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively.

Table 6.16: Features with high importance for predicting extraversion with pupil features.

Study 3	
Feature	Coefficient
B1_c_diameter_mean	0.03
B1_c_blink_max	0.04
TT_c_diameter_max	0.04
TT_c_diameter_min	0.04
TT_c_area_peaks_max	0.04
B5_a_diameter_var_max	0.05
TT_nr_peaks	0.05
B3_a_diameter_var_mean	0.06
B3_f_area_peaks_std	0.06
B1_f_diameter_var_mean	0.06
TT_a_area_peaks_min	0.08
TT_c_diameter_var_mean	0.08
B4_a_blink_max	0.08
TT_c_diameter_var_max	0.08
TT_a_diameter_var_mean	0.10

The results of the predictive models based on the Electrocardiogram (ECG) features represented in Figure 6.8 show a high dispersion of predictive values for most of the scales by looking at the observed versus predicted values. For the five traits, three different model algorithms achieve the best results, from the more simple to the more complex one (MLR, ridge and GB) which complexity, as seen by Table 6.17, are not directly related to lower errors. The set of best features also depends on the trait, covering from 6 to 82 features.

Table 6.17: Details about the best predictive model based on the ECG features during the IGT for each personality scale in Study 3. *CC* are the features resulted from the feature selection based on the correlation coefficient and *GFS* are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	Ridge	6	0.62	-	1.44	0.21	0.21	0
C	GB	82	0.63	-	0.76	0.20	0.94	0
E	MLR	38/15	0.51	-	0.10	0.34	1.08	0
A	Ridge	82	0.31	-	0.50	0.13	0.31	2
N	GB	38	0.66	0.77	0.23	0.99	-	0

For openness, the model is just based on six features and trained using ridge regression. Even with a MSE of 0.62 and a tendency verified in the plot of observed vs predicted values, for values below 3 there is only one individual tested and its prediction has high absolute error (1.44). The predictions for values of openness above 3 are closer to the

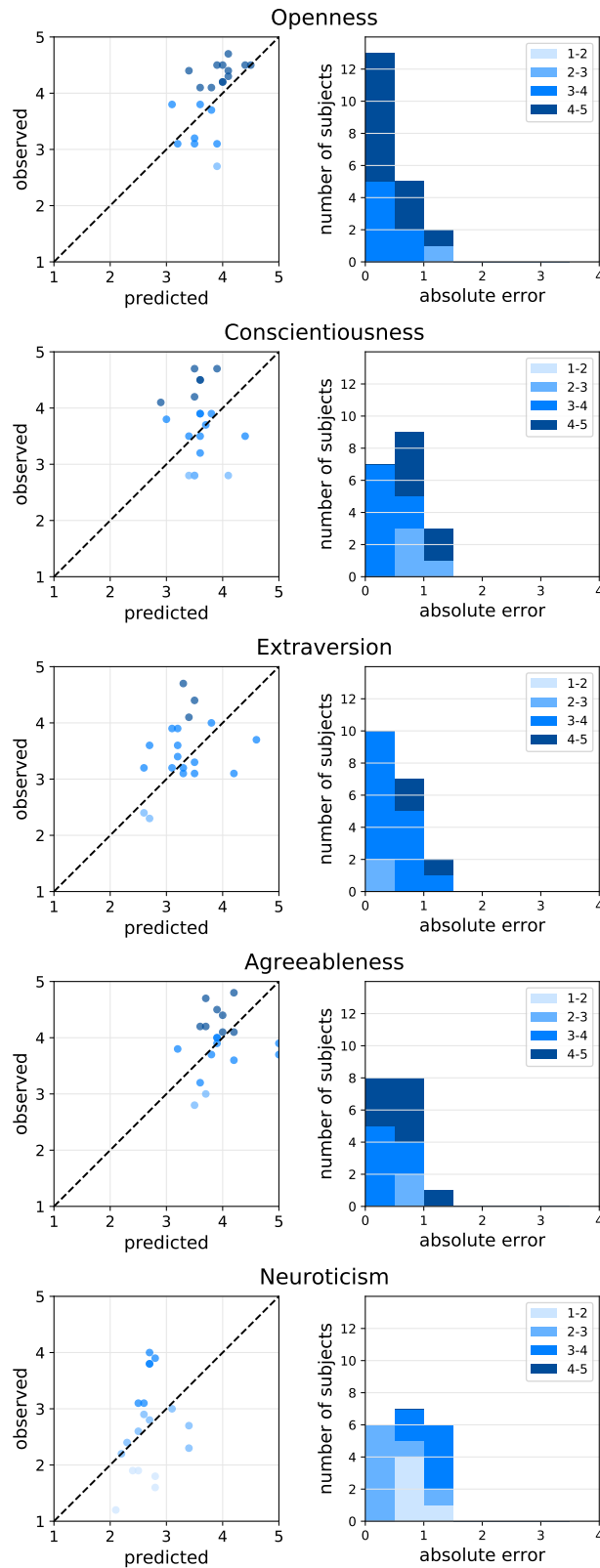


Figure 6.8: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the ECG features during the IGT.

objective line and have a low MSE of 0.21. This is confirmed by the histogram of the absolute errors, in which most of the points have an absolute error smaller than 0.5. As long as the MSE of the range 2-3 is higher than 0.92, the set of features of this model are not explored.

The predictive model of conscientiousness, trained with 82 features and GB predicts most of the points with a value of 3.5, which results in a small MSE for the range of 3-4, but higher errors for more distant ranges, as seen in Figure 6.8. The worst predicted range is the high conscientiousness of 4-5, which two of the five points predicted with an absolute error higher than 1. This also occurs to one-third of the predictions in range 2-3. With a MSE of 0.94 to the range of 4-5, the features of the model are not further explored.

The model of extraversion, as visualized in the plot of observed vs predicted values, has very good results for low values of extraversion, but the higher values to predict, the higher the dispersion found. This model is trained using the simple multiple linear regression with 15 features. While in the range of 2-3 the absolute error of all points is inferior to 0.5, only half of the subjects are classified with this accuracy in the range of 2-3, as observed in the histogram of Figure 6.8. The only three subjects used to test the range of 4-5 in extraversion are away from the ideal line, resulting in a MSE of 1.08. Given this last result, the features of this model are not explored.

Agreeableness is the trait that has all MSE values blow the established threshold, even though there are two existing outliers. Therefore, the model is good enough to explore the more important features. With 82 features from the ECG, ridge regression with alpha equal to 10 was the best predictive algorithm. As observed in the corresponding histogram in Figure 6.8, except for the two outliers, the predictive points are near the ideal line of prediction. Except for one extreme subject high in agreeableness that has an absolute error higher than 1, the remaining subjects have a lower error.

From the 38 features, 32 are the most important (see Table 6.18). This set of features covers all the blocks, but around 30% of the features are from block 4 and 20% are from block 1 and 3. Furthermore, despite all types of features are selected, 40% are from frequency domain and 31% are non-linear features. No previous studies described the importance of features in predictive models of agreeableness trait based on ECG features.

The trait of neuroticism is not well predicted based on ECG features. The best model algorithm was GB with 38 ECG features. As seen in Figure 6.8, even with most of the points being very close to the ideal line of prediction in range 2-3, the other ranges have higher errors, as verified in the histogram in which the ranges between 1-2 and 3-4 are classified with absolute errors between 0.5 and 1.5. The predicted values for neuroticism higher than 3 were all very similar, which resulted in a MSE of 0.99, not acceptable for further feature analysis.

Table 6.18: Features with high importance for predicting agreeableness with ECG features.

Study 3			
Feature	Coefficient	Feature	Coefficient
B2_sd1/sd2	0.04	B1_samp_en	0.07
B1_hf_max	-0.04	B3_he	0.07
B3_hr_std	0.04	B5_hf_max	0.07
B4_dfa	-0.04	B1_tinn	-0.07
B3_%lf	-0.04	B3_triang_index	0.07
B4_hr_min	-0.04	TT_vlf_max	-0.07
B4_%vlf	-0.04	B3_vlf_max	-0.07
B4_sd1/sd2	0.05	B1_%lf	0.07
B4_tinn	0.05	TT_hr_max	-0.07
B4_auto-corr	-0.05	B1_lf_max	0.08
B4_lf_max	-0.05	B2_φ	0.08
TT_lf_max	0.05	B2_hf_max	0.08
B5_lf_max	-0.05	B5_he	-0.09
B5_lle	0.06	B4_vlf_max	0.10
B3_dfa	-0.06	B1_he	0.10
B4_he	0.07	TT_lle	-0.10

6.3.6 Model based on blood volume pulse features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 3 from 114 features to 63, 39, 24, 10 and 6 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively.

Generally looking to the plots of the observed versus predicted values of the big-five personalities in Figure 6.9, the features extracted from Blood Volume Pulse (BVP) are, apparently, the ones that best predict personality. Except for extraversion, the remaining four traits are clearly close to the ideal line of prediction, which is verified by the MSE presented in Table 6.19.

Table 6.19: Details about the best predictive model based on the BVP features during the IGT for each personality scale in Study 3.

Scale	Model	Features	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	GB	63	0.30	-	0.16	0.22	0.51	0
C	Lasso	39	0.47	-	0.70	0.22	0.51	3
E	SVR	63	0.78	-	0.92	0.32	1.10	1
A	SVR	10	0.49	-	0.81	0.17	0.51	1
N	SVR	39	0.23	0.18	0.30	0.23	-	1

Openness is one more time, one of the traits that are best predicted using BVP features.

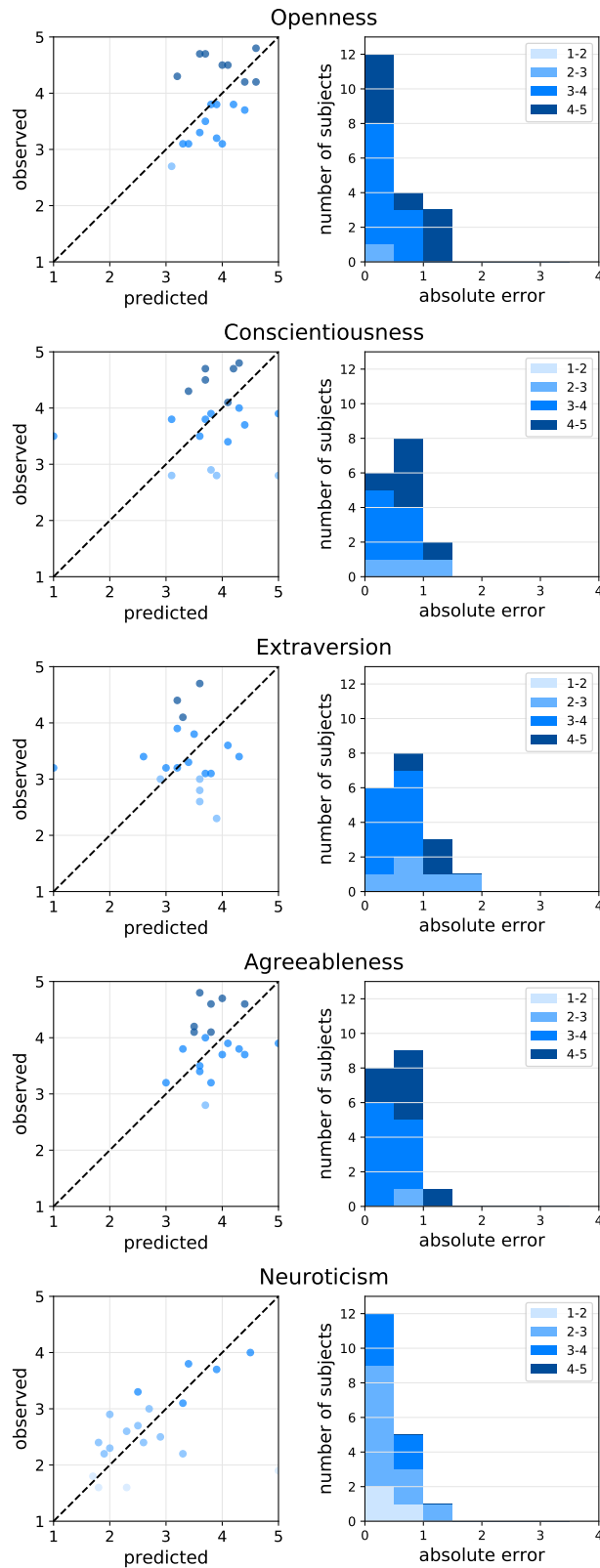


Figure 6.9: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the BVP features during the IGT.

Using a complex algorithm, GB, and with 63 features, no subjects were classified out of defined range and the average MSE is very low. Although the range of 2-3 has just one point to evaluate the model, this is really close to the observed value. The next range, of 3-4 has higher MSE, but still, only 3 out of 10 points have an absolute error higher than 0.5. The most extreme openness subject has a greater MSE of 0.5, with 3 of 8 subjects classified with an error superior to 1.

Of the 63 features, the most important features are presented in Table 6.20. The low interpretability of GB just allow us to know what kind of features are more important to the model, but not how, as already stated. The five blocks and the total game demonstrate to be all important phases to extract features and, therefore, we cannot make any conclusion regarding the phase of the game in which participants manifest more their personality. Although we can not assure the relationship between stronger BVP pulses and high openness trait [283], approximately 40% of the selected features are a statistical result of the pulse width, so the duration of the peaks is an important metric to measure the level of openness.

Table 6.20: Features with high importance for predicting openness with BVP features.

Study 3	
Feature	Coefficient
B4_bav_min	0.024
B2_ibi_std	0.028
TT_pulse_width_min	0.029
TT_pulse_width_std	0.031
B3_pulse_width_std	0.033
B4_bvp_mean	0.033
B5_pulse_width_min	0.035
B2_bvp_mean	0.045
B2_bav_std	0.045
TT_ibi_mean	0.060
B1_pulse_width_min	0.060
B1_bvp_ampl	0.063
B2_bav_min	0.075

The model that best predicts conscientiousness used 39 features and lasso regression algorithm, with a small value of alpha ($\alpha=0.016$), which means that few features will have coefficient zero. Analysing the plot of the observed versus predicted values and the respective histogram of errors in Figure 6.9, the range with worse results are of 2-3 in conscientiousness. First, one subject is an outlier, then regarding the remaining three subjects, only one is very close to the observed value. The MSE of the range 3-4 and 4-5 are exactly the same as openness model, but in this model two individuals are classified out of the expected values in the range of 3-4, which respective error is not used to calculate the MSE. Nevertheless, the MSE of all the ranges are inferior to 0.92 and the most important features are further analysed.

Taking into consideration that from the initial 39 features, 10 had a coefficient equal to zero and that from the remaining 29, only 9 are reported in Table 6.21. The most important feature is the average of the signal in block 2, which is negatively correlated with conscientiousness. This correlation keeps negative in the third block of the game. The standard deviation of the amplitude variation in block 3 is strongly correlated with conscientiousness. Still, regarding block 3, the difference between the maximum and minimum amplitude is short for high conscientiousness subjects but is high if considering the total game. The inter-beat interval is relevant for the total game, with low minimum and mean for high conscientiousness. At last, the maximum pulse duration is high in block 4 for high conscientiousness and with little deviation from the mean in block 5.

Table 6.21: Features with high importance for predicting conscientiousness with BVP features.

Study 3	
Feature	Coefficient
B5_pulse_width_std	-0.15
TT_ibi_mean	-0.15
B4_pulse_width_max	0.15
B3_bvp_mean	-0.17
TT_bvp_ampl	0.19
TT_ibi_min	-0.20
B3_bvp_ampl	-0.30
B3_bav_std	0.37
B2_bvp_mean	-0.49

Extraversion is predicted with 63 features trained by SVR algorithm. As seen in Table 6.19, only one range (3-4) has a MSE inferior to 0.92, but it is where a subject is classified out of the range. This is confirmed by the plots in Figure 6.9, where most of the individuals in the ranges 2-3 and 4-5 are predicted near 3.5. The absolute errors are dispersed in the ranges between 1 and 2 and two-thirds of the high extraverted subjects have an absolute error superior to 1.

Although with some dispersion around the ideal line, the overall MSE is low for the predictive model of agreeableness, based only in 10 features trained with SVR. The one existing subject to test agreeableness below 3 has a predictive absolute error of 0.81, which is acceptable. Despite having an outlier, the range of 3-4 has a small MSE and all the points have an associated absolute error inferior to 1. For high agreeableness, one of seven individuals has an absolute error superior to 1.

Given the low MSE of all the ranges of the model, the relevant features are presented in Table 6.22. No features from the first part of the game (blocks 1 and 2) are contemplated. Prediction of agreeableness is mostly explained by the statistical analysis of the pulse width and the BVP signal. The average of the BVP signal is negatively correlated to agreeableness in the total game and block 3, but it is positively correlated in the last

block of the game. The maximum pulse duration in blocks 3 and 4 is higher for higher agreeableness subjects. Also, the minimum inter-beat interval is regarded as higher for individuals with high agreeableness. The association between high agreeableness subjects and large pulses in BVP supports the conclusion of Stemmler et al. [241], that found an inverse relation between pulse velocity for agreeableness.

Table 6.22: Features with high importance for predicting agreeableness with BVP features.

Study 3	
Feature	Coefficient
B4_pulse_width_max	0.11
B3_pulse_width_max	0.13
TT_bvp_std	-0.14
B3_bvp_mean	-0.17
TT_ibi_min	0.20
B5_bvp_mean	0.28
TT_bvp_mean	-0.32

Neuroticism is the trait predicted with least MSE using 39 BVP features and SVR algorithm. The points represented in the plot of observed versus predicted values in Figure 6.9 are clearly distributed close to the ideal line of prediction. For the low neurotic subjects (range 1-2) excluding one subject that is classified out of the range, the remaining points have a MSE of 0.18. This error is greater for higher neurotics subjects, in which one subject has an absolute error superior to 1. Even so, most of the predictions have an absolute error inferior to 0.5.

In relation to the most relevant features to predict neuroticism, presented in Table 6.23, these are all based on the time related features, i.e. pulse duration and inter-beat interval, as opposite to the results of [241], that found lower BVP amplitude for high neurotics. The deviation from the mean of the pulses width has a high positive correlation with neuroticism. Given that for the total game the maximum of the pulse duration is negatively correlated with neuroticism, the results indicate that neurotics have shorter BVP pulses. However, this is not verified in the end of the game, where the maximum pulse duration is higher for high neurotics and its standard deviation is very short for high neurotics. The frequency of pulses is high for high neurotics, with a minimum of inter-beats interval negatively correlated with neuroticism. The standard deviation is negatively correlated with neuroticism for the whole game, whereas it is higher for neurotics in the beginning of the game (blocks 1 and 2).

6.3.7 Model based on electrodermal activity features

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features of Study 3 from 189 features to 129, 73, 43, 17 and 8

Table 6.23: Features with high importance for predicting neuroticism with BVP features.

Study 3	
Feature	Coefficient
B2_ibi_std	0.27
B2_pulse_width_max	-0.30
B1_pulse_width_min	0.33
TT_pulse_width_max	-0.35
B5_pulse_width_max	0.38
B3_pulse_width_min	0.41
B1_ibi_std	0.49
TT_ibi_std	-0.55
B5_pulse_width_std	-0.61
TT_ibi_min	-0.69
TT_pulse_width_std	0.84

features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively.

The resulting big-five predictive models based on the Electrodermal Activity (EDA) features are presented in Figure 6.10. Observing the plots of the observed versus predicted values, except for neuroticism all scales display a tendency around the ideal line of prediction but with some deviation, which is verified by the existence of absolute errors higher than 1 for all the scales. It was required complex algorithms to predict all traits (GB and ridge) and no outliers are registered in any model.

Table 6.24: Details about the best predictive model based on the EDA features during the IGT for each personality scale in Study 3.

Scale	Model	Features	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	GB	129	0.44	-	0.49	0.46	0.36	0
C	GB	43	0.39	-	0.33	0.09	0.74	0
E	Ridge	17	0.50	-	0.84	0.14	0.53	0
A	Ridge	43	0.58	1.21	0.31	0.21	0.59	0
N	GB	8	1.44	0.33	1.05	1.69	-	0

The algorithm that best predicts openness is gradient boosting, with 129 features. The overall MSE is 0.44 and, by looking at Figure 6.10, it is possible to conclude that values below 4 have a tendency to be predicted as higher values (below the ideal line) and openness higher than 4 have a tendency to be predicted as lower values (above the ideal line). In spite of this, only one subject of the range 3-4 and 4-5 have an absolute error higher than 1, keeping the errors low and the model acceptable for features exploration.

The most relevant features are presented in Table 6.25. Almost 30% of the features are from the total game and, regarding the type of features use, also around 30% are Skin Conductance Response (SCR)-loss correlation features. The feature with higher importance to predict openness is the number of SCR in the feedback phase, followed by

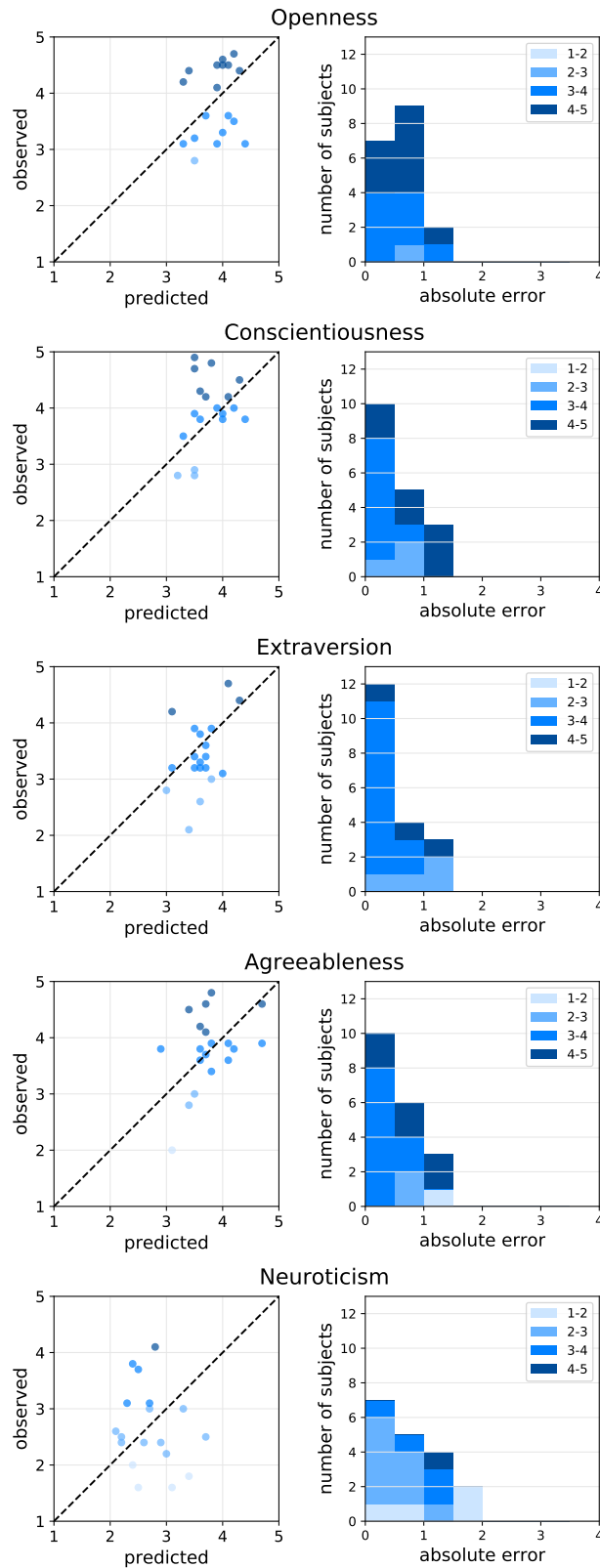


Figure 6.10: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the EDA features during the IGT.

two features of SCR-loss correlation in block 2.

Table 6.25: Features with high importance for predicting openness with EDA features.

Study 3			
Feature	Coefficient	Feature	Coefficient
TT_scr_rate_max	0.02	B1_half_rec_std	0.02
B4_a_scr	0.02	B4_c_scr	0.02
TT_scr_half_rec_std	0.02	B5_scr_rate_std	0.02
B2_mean_loss_corr	0.02	B3_f_scr	0.03
B5_rate_scr_max	0.02	TT_scl_min	0.03
B3_scr_rate_min	0.02	B5_scr_rise_std	0.03
TT_scr_rate_std	0.02	B4_loss_scr	0.03
B5_loss_avg	0.02	B2_a_scr	0.04
B4_mean_loss_corr	0.02	B2_loss_sum_ampl	0.04
B4_half_rec_min	0.02	B2_loss_mean_gauss	0.04
TT_scr_rise_mean	0.02	TT_f_scr	0.05

Also, conscientiousness was best predicted by GB, but with only 43 features. This is the scale predicted with least error by EDA features, attaining a MSE of 0.39. This is confirmed by the plots of the observed versus predicted errors, in which the predictions are close to the ideal line, except for openness higher than 4, with three subjects predicted with an absolute error higher than 1, achieving the maximum MSE of 0.74.

The most important features to predict conscientiousness are presented in Table 6.26. There is no evidence that a specific phase of the game is more informative to predict openness, given that the distribution of features by phases are balanced. However, in this model, more than 40% of the features are SCR-loss correlation features, demonstrating the impact of the EDA responses to losses in predicting conscientiousness.

Table 6.26: Features with high importance for predicting conscientiousness with EDA features.

Study 3			
Feature	Coefficient	Feature	Coefficient
B5_loss_avg	0.03	B1_scl_min	0.04
B4_loss_scr	0.03	B3_f_scr	0.04
B3_mean_loss_corr	0.03	B2_scr_rise_std	0.04
TT_scl_mean	0.03	B1_loss_scr	0.04
B5_mean_loss_corr	0.03	B2_f_scr	0.04
TT_scr_ampl_std	0.03	B5_c_scr	0.04
B4_a_scr	0.03	B1_scr_ampl_min	0.07
B5_f_scr	0.03	B4_mean_loss_corr	0.09
B2_loss_avg	0.04		

The dimension of extraversion was modelled by ridge regression algorithm ($\alpha=10$) and just 17 features. Although around 6 points are more distant to the ideal line of

prediction, as visualized in the plot of observed versus predicted values in Figure 6.10, the remaining points are predicted with low error, very close to the observed value. The range of 3-4 has the majority of subjects, and as confirmed by the histogram of errors, these are mostly predicted with very low error. Even with fewer subjects, the remaining ranges achieved errors inferior to 0.92, so the features of the model are explained.

Of the 17 features used to train the model, 7 are more relevant and are presented in Table 6.27. More than half of the features used are from the total game, showing that extraversion is better predicted if the whole game is considered. The SCR-loss correlation features do not seem to be useful in predicting extraversion, given that the best set of features are morphological-based. The feature that better express extroverts subjects are the minimum half-recovery time, related to the width of the peaks, which is negatively correlated with extraversion. Additionally, for the total game extroverts subjects present a Skin Conductance Level (SCL) lower than introverts. The deviation of the half-recovery time is also negatively correlated with extraversion. Regarding the percentage of peaks, high extraverts have more peaks in anticipation phases of block 1, which keeps consistent in block 3 but, besides, the percentage of SCR in block 3 is also correlated with extraversion.

Table 6.27: Features with high importance for predicting extraversion with EDA features.

Study 3	
Feature	Coefficient
B3_c_scr	0.07
B1_a_scr	0.09
TT_scr_rate_std	0.09
B3_a_scr	0.09
TT_half_rec_std	-0.10
TT_scl_mean	-0.12
TT_half_rec_min	-0.18

The trait agreeableness is predicted with 43 features trained by a ridge regression algorithm with alpha equal to 10. Despite the proximity of most of the points to the ideal line of prediction, the range of 2-3 has only one point, predicted with a high absolute error, as confirmed by the histogram of errors. Along with this point, also two extreme agreeableness subjects (range 4-5) are predicted with an absolute error higher than 1.

Neuroticism, which is the only trait with previous association with anticipatory SCR, did not achieve a good predictive model. The best algorithm to predict neuroticism based on the EDA features was the GB with 8 features, but the minimum MSE is 1.44. The plot of the observed versus predicted values and the respective histogram expose the random distribution of points around the ideal predictive line.

6.3.8 Model based on biosignals features

This model was build by the combination of the features extracted from the physiological signals: pupil, ECG, BVP and EDA.

The feature selection method was used as the first step of the machine learning approach to remove the correlated features from the features' set. With this step, we made a reduction in the sample of features from 825 features to 473, 220, 117, 39 and 8 features when applying a correlation factor of 0.9, 0.7, 0.5, 0.3 and 0.1, respectively.

The resulted big-five predictive models are presented in Figure 6.11. Recalling that the subjects used to train and test these models need to have a correct extraction of features from all biosignals, the total sample has just 45 subjects. Observing the plots of the observed versus predicted values, openness, extraversion and agreeableness, even with some dispersion, present a tendency to predict the values around the ideal line of prediction.

Details about the predictive models, presented in Table 6.28, Different algorithms are best to predict the different scales of personality, but ridge regression and SVR attain the least MSE. Except for agreeableness, most of the model performed better with a large set of features.

Table 6.28: Details about the best predictive model based on the biosignals features during the IGT for each personality scale in Study 3. *CC* are the features resulted from the feature selection based on the correlation coefficient and *GFS* are the features resulted from the greedy forward selection method.

Scale	Model	Features CC/GFS	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
O	SVR	473	0.34	-	0.49	0.32	0.21	1
C	MLR	473/17	0.86	2.25	0.49	0.46	0.23	4
E	Ridge	473	0.40	-	0.43	0.22	0.57	1
A	Ridge	39	0.18	-	0.04	0.26	0.24	3
N	GB	220	0.78	0.67	0.16	1.53	-	0

To predict openness, the model algorithm SVR combined 473 and ended up with a MSE of 0.34. By looking at the plot of the observed versus predictive values, the low obtained MSE is in accordance with the proximity of the predictions from the ideal line of prediction. As was the case of more than one isolated signal, there were no subjects in the range of 2-3 and only one subject is used to test the range of 2-3, which with all biosignals had an absolute error of 0.49. The range of 3-4 has a lower MSE, but still has one subject with an error higher than 1. The last range, of 4-5 only one individual is predicted with an absolute error higher than 0.5, whereas an outlier exists in this range.

Given the small MSE for all ranges, the features are further explored. With a set of 473 features, the more relevant ones are still a large set of 145 features, which becomes more complicated to understand how the model distinguish between low and high openness

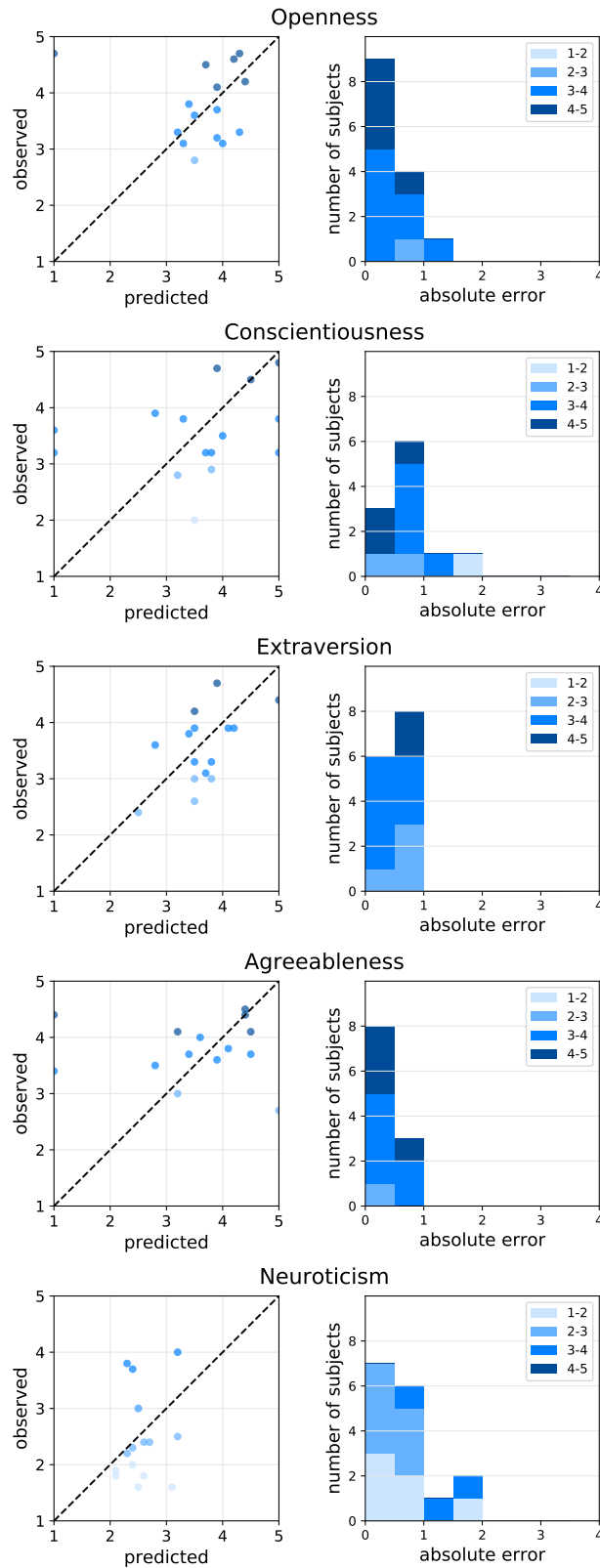


Figure 6.11: Plot of the observed versus predict values of personality and respective histogram of the absolute error for Study 3 based on the biosignals features during the IGT.

subjects. In terms of phases of the game, although all the block of the game has an impact on modelling openness, 32% of the features are from block 1 and, the minimum impact is 12% for features from block 5. This is in concordance with the theory of [24] that personality is more expressed under conditions of more ambiguity. The biosignal that has more impact in the model is the EDA, comprising 33% of the best features of the model. Following is ECG, with 26% of the features and right after pupil with 25%. Even with lower impact, BVP still covers 16% of the features. These results are in conformity with [243, 261], that have better classifications for EDA than ECG predicting openness.

The scale of conscientiousness was predicted by the simple algorithm MLR, with a reduction by forward selection from 473 to 17 features. Even with not many tested points, the plot of the observed versus predicted values for conscientiousness, it is still verified a tendency of distribution around the ideal line of prediction. The histogram confirms that for two of the ranges(2-3 and 4-5) all points are predicted with an absolute error inferior to 1. Even with an error higher than 1 for the range of 3-4, the MSE was small, if not regarding the existent four outliers. With just one subject to test, the range of 2-3 has an absolute error of 2.25, and therefore the features of this model are not explored.

The best prediction of extraversion, in similarity with the openness model, has 473 features but it trained based on a ridge regression with alpha equal to 10. The histogram of the errors shows that all the ranges are predicted with an error inferior to 1, without regarding the outlier in the range of 4-5. As confirmed in the plot of the observed versus predicted values, the predictions are close to the observed values. Furthermore, 5 of the 14 subjects tested are classified as 3.5, even being two from the range of 2-3, two from the range of 3-4 and one for the range of 4-5, these all had an absolute error inferior to 1.

With all MSE below 0.92, the predictive model of extraversion is good enough to explore the features. With a set of relevant features equal to 145, we face exactly the same problem we had interpreting the openness model. In this model, the distribution of features is more uniform, but still, block 1 has a higher percentage of features (almost 20%), while block 2 has the lower percentage of features (12%). In this case, we can not conclude that extraversion is more expressed under conditions of more ambiguity since the influence of block 1 is not high and block 2 has the least impact on the model. About the biosignals with greater impact on the model, EDA features explain 37% of the best features, but ECG features also have a great impact, being 34% of the best features. Pupil and BVP have less impact in modelling extraversion, explaining 15% and 14% of the features, respectively. However, these results are against previous studies [168, 243, 261] that predicted with more accuracy extraversion using ECG features instead of using EDA features.

Agreeableness is best predicted with the same model algorithm as extraversion, ridge regression, but with just 39 features. There are four subjects classified out of the range, but without contemplating them, this is the trait that has the best predictive model, i.e. least MSE, using the combination of all biosignals features. Observing the plot of the observed versus predicted errors, a single subject is very close to the observed value for

Table 6.29: Features with high importance for predicting openness with biosignals features.

Study 3			
Feature	Coefficient	Feature	Coefficient
pupil_B1_f_area_peaks_min	0.008	ecg_B4_cd	-0.011
pupil_B1_a_diameter_var_max	-0.008	pupil_TT_c_diameter_min	-0.012
pupil_B5_a_area_peaks_std	0.009	ecg_B2_hf_max	-0.012
ecg_TT_triange_index	-0.009	eda_B5_scl_min	-0.012
eda_B5_scr_rise_mean	-0.009	bvp_TT_bvp_ampl	-0.012
bvp_B3_pulse_width_min	-0.009	ecg_B2_lf_max	0.012
eda_B1_scr_half_rec_std	0.009	bvp_B1_pulse_width_min	-0.012
eda_B2_scr_rise_min	-0.009	pupil_B5_c_diameter_min	-0.012
pupil_B3_f_diameter_var_min	-0.009	ecg_B3_dfa	-0.012
eda_B2_scr_ampl_std	-0.009	eda_B3_scr_half_rec_mean	0.012
eda_TT_scr_rise_mean	0.009	pupil_B4_c_diameter_var_mean	-0.012
eda_B3_scr_half_rec_min	0.009	ecg_B5_hf_max	0.012
eda_B1_loss_avg	0.009	pupil_B4_c_area_peaks_min	0.012
ecg_B3_cd	-0.009	eda_B1_scr_half_rec_mean	0.013
bvp_B3_pulse_width_std	0.009	pupil_TT_c_area_peaks_max	0.013
ecg_B4_triange_index	-0.009	pupil_B1_a_area_peaks_min	0.013
pupil_B1_c_area_peaks_min	0.009	eda_B4_scr_ampl_min	-0.013
pupil_B1_c_diameter_var_mean	-0.009	ecg_B1_lf/hf	0.013
ecg_B3_samp_en	0.009	ecg_B3_vlf_max	0.013
ecg_B5_lf_max	-0.009	eda_B5_scr_ampl_mean	-0.013
eda_B4_f_scr	-0.009	eda_B2_scr_half_rec_min	-0.013
eda_B4_loss_sum_squared	-0.009	ecg_B5_hr_max	0.013
ecg_TT_ap_en	0.009	ecg_B2_lf/hf	0.013
eda_TT_scl_std	-0.009	eda_B3_scr_rise_mean	0.013
eda_B5_scr_rate_min	0.009	ecg_B1_lf_nu	0.013
eda_B4_loss_mean_scr_ampl	-0.010	pupil_B3_a_diameter_var_mean	-0.013
eda_B2_loss_sum_scr_ampl	0.010	ecg_B4_hr_max	0.013
bvp_B1_pulse_width_max	-0.010	ecg_B5_hr_std	0.013
bvp_B2_bvp_mean	-0.010	ecg_B1_auto-corr	-0.014
ecg_B1_φ	-0.010	eda_B3_scr_ampl_min	0.014
pupil_B2_f_diameter_min	-0.010	eda_B4_loss_sum_scr_ampl	-0.014
bvp_B1_pulse_width_std	0.010	bvp_B5_pulse_width_min	-0.014
pupil_B1_f_diameter_min	-0.010	pupil_B4_a_diameter_var_max	-0.014
ecg_B2_%lf	0.010	eda_TT_scr_ampl_max	-0.014
pupil_TT_c_diameter_mean	-0.010	eda_B4_a_scr	0.014
bvp_TT_ibi_mean	-0.010	bvp_B2_pulse_width_min	-0.014
pupil_B3_c_area_peaks_max	0.010	eda_B3_scl_min	-0.014
ecg_B4_ap_en	0.010	ecg_B5_ap_en	0.015
pupil_TT_c_area_peaks_mean	0.010	eda_B1_scr_rise_std	0.015
eda_B1_a_scr	0.010	eda_B4_loss_scr	-0.015
pupil_B5_c_area_peaks_max	0.010	eda_B2_mean_loss_corr	0.015
bvp_B3_ibi_std	-0.010	bvp_B3_bvp_ampl	-0.015
eda_B3_c_scr	0.010	eda_TT_scr_ampl_std	-0.015
pupil_B1_c_area_peaks_std	0.010	bvp_TT_pulse_width_min	-0.015
eda_B4_scr_rise_min	-0.010	pupil_B3_c_area_peaks_min	0.015
ecg_B5_triange_index	-0.010	eda_B4_scr_half_rec_min	-0.015
pupil_B2_a_diameter_var_mean	-0.010	bvp_TT_pulse_width_max	0.015
bvp_B2_ibi_min	-0.010	pupil_B2_f_diameter_mean	-0.016
ecg_B3_lf	-0.010	bvp_B2_pulse_width_std	0.016
bvp_B5_ibi_std	-0.011	eda_TT_scl_mean	-0.016
eda_B2_loss_mean_scr_ampl	0.011	bvp_TT_pulse_width_std	0.016
pupil_TT_a_diameter_min	-0.011	eda_B1_scl_min	-0.017
ecg_B3_lf_max	0.011	ecg_B4_hf_max	0.017
pupil_TT_c_diameter_var_mean	-0.011	eda_B2_loss_scr	0.017
eda_B5_scr_rise_std	-0.011	pupil_B2_c_area_peaks_min	0.017
ecg_B1_%hf	-0.011	eda_B5_f_scr	0.017
pupil_TT_a_area_peaks_max	0.011	pupil_B4_a_diameter_var_mean	-0.017
ecg_B1_samp_en	0.011	bvp_TT_bvp_mean	-0.017
ecg_B1_%lf	0.011	bvp_B1_bvp_mean	-0.018
ecg_B4_dfa	-0.011	ecg_B1_hf_max	-0.018
ecg_B1_cd	-0.011	bvp_B1_bvp_ampl	-0.018
eda_B2_scr_ampl_min	-0.011	eda_B2_loss_mean_gaussian	0.019
pupil_B2_c_diameter_max	-0.011	bvp_B2_ibi_mean	-0.020
eda_B3_loss_mean_gaussian	-0.011	pupil_TT_a_diameter_var_mean	-0.021
pupil_B1_f_diameter_var_max	-0.011	ecg_B1_si	-0.021
pupil_B1_c_nr_peaks	0.011	eda_TT_scl_min	-0.022
pupil_B3_f_diameter_min	-0.011	eda_B2_c_scr	-0.022
pupil_B4_c_diameter_mean	-0.011	ecg_B2_vlf_max	0.024
ecg_B1_vlf	0.011	ecg_B1_lle	0.024
eda_B4_scr_ampl_std	-0.011	ecg_B5_vlf_max	0.025
eda_B4_mean_loss_corr	-0.011	bvp_B2_ibi_std	-0.025
eda_TT_a_scr	0.011	eda_B4_scl_min	-0.028
pupil_B3_a_area_peaks_min	0.011		

6.3. MODELLING PERSONALITY RESULTS

Table 6.30: Features with high importance for predicting extraversion with biosignals features.

Feature	Study 3		Coefficient
	Coefficient	Feature	
ecg_B3_lf_max	0.008	pupil_B2_a_area_peaks_std	-0.011
ecg_B5_he	0.008	ecg_B5_hr_max	0.011
bvp_B3_bav_std	0.008	eda_B5_c_scr	0.011
pupil_B5_c_diameter_var_mean	-0.008	bvp_B3_bvp_mean	0.011
eda_B5_scr	0.008	bvp_B4_ibi_min	0.011
pupil_B4_c_diameter_mean	-0.008	pupil_B2_a_nr_peaks	-0.011
ecg_B4_lle	0.008	bvp_B2_ibi_mean	0.011
pupil_B2_a_diameter_min	0.008	ecg_TT_lf/hf	-0.011
bvp_B3_pulse_width_max	-0.008	ecg_TT_nn50	0.011
bvp_B1_bvp_mean	-0.008	pupil_B3_c_diameter_var_mean	-0.011
eda_B5_loss_avg	-0.008	ecg_B5_ap_en	0.012
eda_B3_scr_half_rec_min	-0.008	bvp_B4_bvp_ampl	0.012
pupil_B5_c_diameter_var_max	0.008	ecg_B4_%hf	0.012
pupil_TT_a_area_peaks_min	0.008	ecg_B2_auto-corr	0.012
pupil_B1_f_diameter_variation_min	0.008	eda_B5_scr_rate_mean	0.012
eda_B5_scr_half_rec_mean	0.008	eda_B5_mean_loss_corr	-0.012
ecg_TT_hr_max	0.008	eda_B1_scr_rise_std	-0.012
ecg_B1_total_power	-0.008	ecg_B4_%vlf	-0.012
pupil_B3_f_diameter_variation_min	-0.008	ecg_B4_lf/hf	-0.012
eda_B5_scr_rise_min	0.008	ecg_B4_sd1/sd2	0.012
ecg_TT_cd	-0.008	eda_B5_scr_rate_std	0.012
eda_B2_scr	0.009	ecg_B1_auto-corr	-0.012
ecg_B4_samp_en	0.009	ecg_B2_lf_max	0.012
eda_B4_scr_rise_mean	-0.009	ecg_B1_cd	-0.012
ecg_TT_hr_min	-0.009	ecg_B4_vlf_max	0.013
ecg_B1_lf_nu	0.009	eda_B1_scr_ampl_min	0.013
ecg_TT_ap_en	0.009	eda_B1_scr_rise_mean	-0.013
pupil_B1_c_diameter_var_max	-0.009	ecg_B5_hf_max	0.013
bvp_TT_ibi_std	-0.009	eda_B5_f_scr	0.013
bvp_B3_pulse_width_min	-0.009	bvp_B1_bav_std	-0.013
eda_B4_c_scr	0.009	bvp_B5_pulse_width_max	-0.013
eda_B2_scr_half_rec_std	-0.009	eda_B1_a_scr	0.013
ecg_B2_hf_max	0.009	eda_B4_scr_rise_min	-0.013
bvp_TT_pulse_width_mean	0.009	eda_TT_a_scr	0.013
ecg_B1_pnn50	0.009	ecg_TT_vlf_max	-0.013
ecg_B3_%lf	-0.009	eda_B1_scr_half_rec_mean	-0.013
bvp_B2_ibi_min	0.009	pupil_B5_a_diameter_var_max	0.014
ecg_B5_lf	-0.009	eda_B3_a_scr	0.014
eda_B1_c_scr	-0.009	eda_B3_scr_half_rec_max	0.014
eda_TT_scr_rate_mean	0.009	bvp_TT_pulse_width_min	-0.014
pupil_B1_a_area_peaks_min	0.009	ecg_B5_lle	-0.014
pupil_B4_a_diameter_var_min	-0.009	eda_B5_scr_half_rec_std	0.014
pupil_B4_f_diameter_min	-0.009	eda_B2_scr_ampl_min	0.014
bvp_B1_ibi_min	0.009	eda_TT_scr_rise_min	-0.014
eda_TT_c_scr	-0.009	ecg_B2_lle	-0.014
pupil_B5_a_diameter_var_min	-0.009	eda_B3_scr_rate_mean	0.014
ecg_B1_lf	-0.009	eda_B4_scr_ampl_min	-0.015
bvp_B2_bvp_mean	-0.010	eda_B3_loss_scr	0.015
bvp_B1_ibi_std	-0.010	eda_B3_scr_rate_min	0.016
bvp_B1_bvp_ampl	-0.010	ecg_B3_he	0.016
pupil_B2_f_diameter_var_min	-0.010	eda_B1_scr_half_rec_max	-0.016
pupil_B1_a_diameter_min	0.010	ecg_B3_lle	-0.016
ecg_B5_lf/hf	-0.010	bvp_B5_ibi_std	-0.016
ecg_TT_φ	-0.010	ecg_B3_%vlf	0.016
pupil_TT_f_nr_peaks	-0.010	eda_B3_scl_min	-0.016
eda_B4_scr_rate_std	0.010	eda_B2_scl_min	-0.016
pupil_TT_c_diameter_var_mean	-0.010	ecg_B4_auto-corr	-0.016
eda_B3_scr_rate_std	0.010	eda_B3_scr_half_rec_std	0.016
bvp_B4_ibi_max	-0.010	eda_B1_scr_half_rec_min	-0.017
ecg_B3_ap_en	0.010	eda_B4_scr_rate_mean	-0.017
ecg_TT_samp_en	0.010	eda_B3_scr_rate_max	0.017
pupil_B1_c_diameter_min	0.010	eda_B4_f_scr	-0.018
eda_B2_scr_rate_std	-0.010	ecg_B4_he	-0.018
eda_B1_scr_ampl_std	-0.010	ecg_B5_hr_std	0.018
eda_B2_c_scr	-0.010	eda_B4_scr_half_rec_min	-0.019
ecg_TT_lle	-0.010	eda_TT_scl_min	-0.019
eda_TT_scr_ampl_max	-0.010	eda_B1_scl_min	-0.020
eda_B3_mean_loss_corr	0.010	ecg_B1_si	-0.020
eda_TT_scl_mean	-0.011	pupil_B2_f_diameter_var_mean	-0.020
eda_B4_loss_mean_scr_ampl	-0.011	eda_B4_scr_rate_min	-0.022
ecg_B4_dfa	-0.011	ecg_TT_lf_max	0.023
ecg_TT_hr_mean	-0.011	ecg_TT_si	-0.025
ecg_B1_hr_std	0.011		

the range of 2-3, with an absolute error inferior to 0.5. The range of 3-4 has two more disperse values, but their error are below 1. For the extreme agreeableness subjects, three subjects are close to the ideal line of prediction, with only one subject predicted with an absolute error higher than 0.5.

The more relevant features to predict agreeableness are presented in Table 6.31. Every block of the game has at least one associated feature but almost 40% of the features are extracted from the whole game. About the biosignals with greater impact in the model are again EDA features that have more impact in the model, this time with 39%. ECG and BVP features have a more similar impact, with 31% and 29% of the best features, respectively. At last, pupil features only explains 7% of this model. The feature with higher correlation with agreeableness is from ECG, the maximum high frequency in block 5.

Table 6.31: Features with high importance for predicting agreeableness with biosignals features.

Study 3	
Feature	Coefficient
pupil_TT_a_diameter_mean	0.09
eda_B5_scr_ampl_min	-0.10
bvp_B1_pulse_width_max	-0.12
bvp_TT_bvp_mean	-0.13
eda_B4_c_scr	0.14
ecg_B2_vlf_max	0.14
ecg_TT_vlf	-0.15
ecg_TT_hr_std	-0.16
bvp_B2_pulse_width_max	-0.16
eda_B3_c_scr	0.19
eda_TT_half_rec_std	-0.20
eda_B5_mean_loss_corr	-0.23
ecg_B5_hf_max	0.29

The only characteristic in the pupil that differentiates agreeableness subjects is the mean diameter in the anticipation phase, that is higher for high agreeableness subjects. Throughout the game, the mean of the BVP is consistently small for high agreeableness individuals. Additionally, the maximum pulse width at the beginning of the game (block 1 and block 2) is negatively correlated with agreeableness, which is against the conclusion of [241], that found lower pulse velocity for high agreeableness. The ECG features are mainly from the frequency domain. The maximum of high-frequency registered in block 5 is the most important feature distinguishing low and high agreeableness, with high values to high agreeableness subjects. In block 2 the maximum of very low-frequencies is also high for high agreeableness, but the power of this range of frequencies is low if regarding the whole game. In the statistical domain, the deviation from the mean of the heart rate in the total game is bigger for low agreeableness subjects. Concerning EDA

features, most of the features are morphological-based, but the feature with higher impact is the mean of all SCR-loss correlation features calculated in block 5, which is bigger for lower agreeableness. For the whole game, the standard deviation of the half-recovery time is lower for high agreeableness, meaning that the width of the peaks is more variable in low agreeableness subjects. In blocks 3 and 4, the number of SCR is directly correlated with agreeableness. At last, also the minimum amplitude of the SCR in block 5 is small for high agreeableness individuals.

Neuroticism is the only trait which model based on biosignals features has no outliers. It uses the most complex algorithm, GB and a large set of features (220). Despite the low MSE, by looking at the plots in Figure 6.11, we can conclude that the range of observed values (1.5-4) is wider than the range of predicted values (2-3.2) and, and the histogram presents the dispersion of errors while predicting neuroticism. Even so, the range of 2-3 has most of the predictions near the ideal prediction line, with errors below 1. The range of 2-3 has also some good predictions, but one has a predictive absolute error of almost 2. The range with worse results is from 3 and 4, in which two of the three tested subjects have an absolute error between 1 and 2, resulting in a high MSE of 1.53. Regarding the latter results, the features used in this model are not explored.

APPLICATION IN MEDICAL DECISION-MAKING

This chapter includes the results of the application of a predictive model of personality to a study with medical doctors. Diagram 7.1 presents the main purpose of this chapter: can a personality model be applicable to real scenarios of decision-making? As described in 4.3, in Study 4 only the pointer movements are acquired, so the best personalities predictive models built from mouse features are tested in a different context.

For this purpose, some of the predictive models of Study 2, based on mouse movements, are applied to each case scenario of Multimorbidity Interaction Severity Index (MISI) and the personality questionnaire. First, in this chapter the results of the personality questionnaires of Survey 4 are presented. Then, the outputs of Chapter "Modelling Personality using Machine Learning", i.e. the personality models based on pointer interaction are used to test their applicability in a medical decision-making scenario (see diagram A).

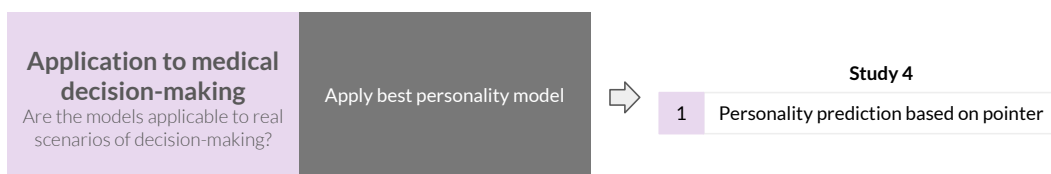


Figure 7.1: Details about what will be explained and what are the outputs of the Chapter "Application in Medical Decision-making" in the context of this thesis.

7.1 Personality results

The Cronbach's alphas [60], a metric that estimates the reliability of a psychometric test, were 0.64, 0.76, 0.87, 0.60 and 0.82 for the Openness, Conscientiousness, Extraversion,

Agreeableness and Neuroticism scales, respectively, in our data from Study 4.

Regarding the thirteen subjects of Study 4, the mean, standard deviation, maximum and minimum of each personality scale are presented in Table 7.1. Figure in 7.2 represent the violin plots of the results of the questionnaires for both studies' personality scales.

Table 7.1: Personality results for Study 4.

Personality	Mean	STD	Minimum	Maximum
Openness	3.8	0.5	3.0	4.7
Conscientiousness	3.9	0.4	3.0	4.8
Extraversion	3.3	0.5	2.4	4.1
Agreeableness	3.9	0.3	3.3	4.3
Neuroticism	2.5	0.5	1.8	3.3

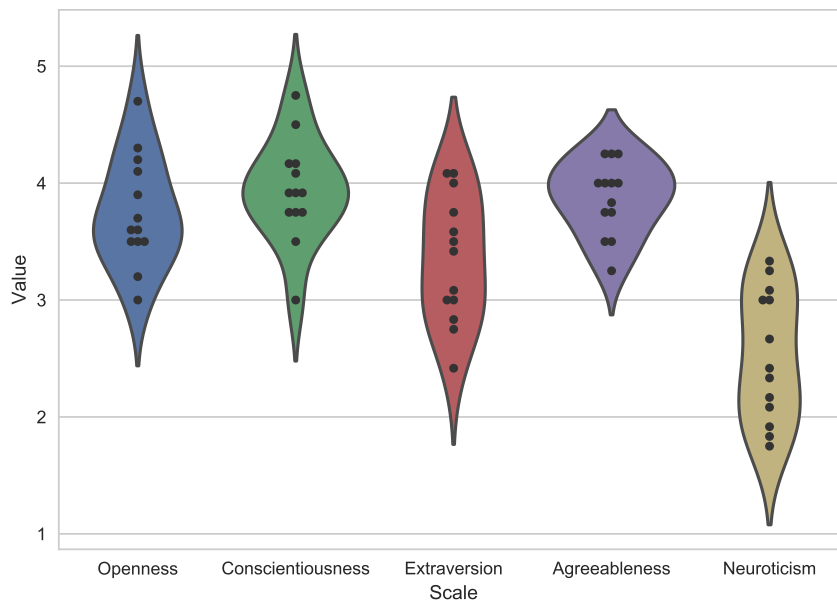


Figure 7.2: Violin plots of each personality scale distribution in Study 4.

The population distribution of most scales results presents a shape similar to a Gaussian curve, meaning that there are few people in above and below the mean of each personality dimension, which is particularly verified for conscientiousness and agreeableness. Even with very few subjects in this study, the mean and standard deviations are similar to what was found in Study 2 and 3. Furthermore, all the ranges covered in the big-five personalities are within the explored ranges in Study 2 and 3, so we considered that these values were previously trained by the different models.

Based solely on the small set of physicians that comprises our data sample, conscientiousness and neuroticism are consistent with [169], that declared that physicians tend to have higher scores on conscious personality trait and lower scores on the neurotic

personality scale. Whilst Mirhaghi et al. [169] considered physicians low in agreeableness personality scale, in our sample this is not verified. The extraversion results are distributed mostly around median values, which explains the disagreement between previous studies [169, 194].

7.2 Model Application to MISI

To extract the features from the pointer interaction, the processing tools described in Chapter 5 are applied, but the design of the cases are slightly different from the NEO-FFI questionnaire, given that instead of one 5-Likert scale, the cases have 4 sub-scales. For this reason, some features need to be adapted to this context and therefore, are divided by the number of sub-scales. The adapted features are only micro-behavioural features: t_item , t_accum , $\#ans_hovered$, $answer_ratio$, t_bef_click , $pause_bef_click$, $distance_answer$, $<-turns$, t_item , $\#correc_between_item$, $\#correc_within_item$, $\#revisits$ and t_correc .

For two reasons, we have decided to use the personality models built based on Study 2. First, the data acquisition setup is similar to Study 2, in which just the computer mouse while interacting with a computer is providing behavioural information about the user and, in contrast to Study 3, no physiological sensors are attached. The second reason is the good accuracy attained in predicting most of the personality traits in Study 2.

With the exception for agreeableness model, that did not achieve good predictive results, of the respective models of the remaining four scales of personality, the best two models (openness and extraversion) were used to predict personality in the NEO-FFI questionnaire and in each case of MISI.

The results of each personality trait prediction in the personality questionnaire and in each case of the MISI are presented in Table 7.2.

Table 7.2: Details about the application of openness and extraversion predictive models based on the pointer movements features in each case of MISI and personality questionnaire in Study 4.

Survey	MSE	MSE [1-2]	MSE [2-3]	MSE [3-4]	MSE [4-5]	Outliers
Openness						
NEO-FFI	0.75	-	1.43	0.78	0.04	2
Low conflict case	0.59	-	1.36	0.19	0.23	7
Medium conflict case	1.28	-	1.91	0.65	-	10
High conflict case	1.27	-	-	1.27	-	9
Extraversion						
NEO-FFI	0.40	-	0.81	0.16	0.22	1
Low conflict case	2.65	-	0.71	4.6	0.23	7
Medium conflict case	2.11	-	1.49	2.73	-	10
High conflict case	3.17	-	0.78	-	5.55	11

The application of the models in the personality questionnaires, but in a specific group of people, constituted by physicians, attained worse results compared with Study 2 with more outliers and bigger Mean Squared Error (MSE), but most of the subjects are well predicted in openness and extraversion, as shown in Figure 7.3.

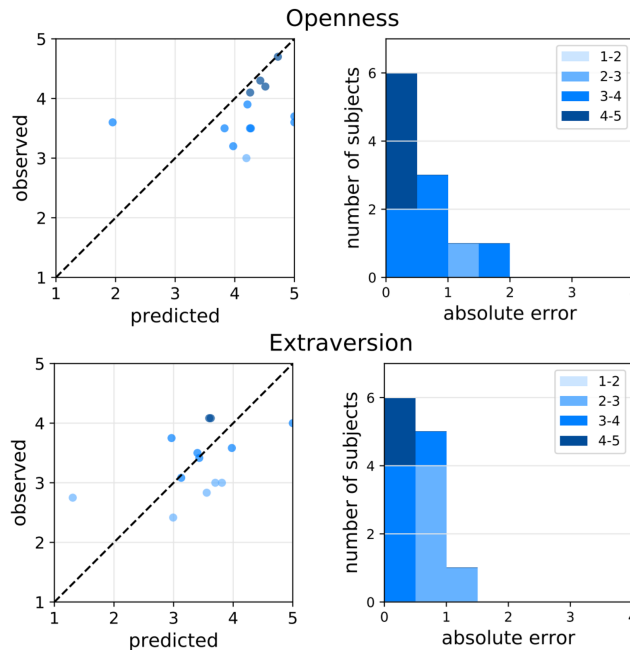


Figure 7.3: Plot of the observed versus predict values of personalities and respective histogram of the absolute error for Study 4 based on the pointer movements features personality questionnaires.

Analysing the results for predicting openness, contrary to what was concluded in Study 2, in this study the range with best results is the one with higher openness subjects, with a really small MSE. For openness below 4, the errors are higher and two outliers are even classified out of the range.

Extraversion outperforms openness predictive model and is the best predicted trait in this study, with a MSE of 0.40. By looking at Figure 7.3, with an exception for two points, the remaining subjects are close to the ideal line of prediction. The two worse predictions correspond to an outlier in the range between 3 and 4, and the other is the only prediction with an absolute error higher than 1.

These findings, even based in a small sample of subjects, support the application of the personality models to a population of medical doctors.

The application of the predictive models of openness and extraversion in a medical context, MISI, resulted in some ranges with low MSE, but concerning the number of outliers, these are probably based on very few subjects. In addition to all the cases that have, at least, a range with high MSE, no conclusions can be drawn based only on a maximum of 6 subjects classified within the range of personality (1-5). Thus, the plots of the observed versus predicted values, as well as the histogram of the errors are not

presented to further analysis.

It is still interesting to note that the number of outliers is similar in both scales of personality, which could mean that the models are applicable only for a restricted type of subjects and, therefore, models trained with a large population will be probably more extensible to other contexts.

Compared with a personality assessment questionnaire, in which most of the questions are straightforward, the evaluation of multimorbidity interactions are, for sure, more complex decisions to make. For both models, openness and extraversion, it is the low conflict case that has lower MSE and more subjects classified within of the range. This could mean that the behaviour of the doctors depends on the complexity of the task they are performing and might be that the personality models built in this thesis are applicable to simpler medical decision-making tasks.

Nonetheless, the great impact of micro-behavioural features in the models reported in Chapter 6 probably had influenced these final results. The normalization of the features regarding sub-scales, made by the division of features by 4, approximates the cognitive demand to answer each sub-scale, to the cognitive demand to answer a single NEO-FFI item. For example, it seems that it is more difficult to evaluate the severity of a Disease–Disease, Drug–Disease, and Drug–Drug Interactions (DDIs), than to tell how certain you are about that answer, so each sub-scale should be carefully considered to correctly extract micro-behavioural features.

CONCLUSIONS

As the last chapter of this thesis, we present a summary of the work developed in line with the main objectives described in Chapter 1. The outcomes are further detailed, as well as the publications released. Then, generally looking to our results, we describe possible applications in which the outcomes of this thesis may be used. Some suggestions to extend the results of this work are presented in future work. To conclude, the implications of the attained work, in terms of the acquisition and analysis of human behaviour, are discussed.

8.1 Overall Results

This thesis main objective was to predict personality in medical decision-making contexts. The whole process to achieve this goal covers the extraction of features from human behaviour, the gathering and linking of relevant information for each personality trait by machine learning algorithms and, at last, the application to a medical decision-making context.

Considering that each study procedure includes computerized decision-making tasks, features that represent human behaviour were extracted from physiological responses (pupil, Electrocardiogram (ECG), Blood Volume Pulse (BVP), and Electrodermal Activity (EDA)) and human-computer interaction (pointer movements and decision-making task variables). Except for the pointer interaction in the decision-making task, the remaining sources of data proved to have a relationship with personality traits. Features from BVP and pointer interaction in online surveys achieved the best results in modelling personality, with high accuracy for four of the five big personalities.

The computation of context-related features generated an extensive set of features that, regarding the small sample of observations in each study, can cause over-fitting in modelling personality. To avoid this, k-fold cross-validation is applied to evaluate the

models. Within each set of features, the variety and diversity of the best features of each personality trait models confirm the relevance of exploring the data and extract many features.

The use of different correlation coefficients to select features and different algorithms to train the models demonstrated to be a strategy that leads to better outcomes. For each group of features, each personality trait is best modelled by a specific algorithm and set of features filtered by a specific coefficient.

In our study, openness to experience was the trait that is well predicted more frequently using different data sets. Openness to experience reflects the appreciation of new experiences, exploration of the unfamiliar and greater tolerance of conditions of uncertainty and ambiguity [162]. Individuals with high trait openness have a mental and experiential life that can be described as creative, original, and complex. Some researchers could not find a relation between this dimension and IOWA Gambling Task (IGT) inefficiency [70, 120, 194], but Yilmaz et al. [277] found that high openness individuals tend to have worse decision-making skills. Our results confirm the relation between openness and decision-making skills and also achieved good predictive results using features from the IGT. In relation to physiological arousal, previous studies had good results predicting this trait by EDA features [243, 261], by ECG features [168] or just found an association between ECG or BVP and openness [232, 283]. Good predictive models were achieved using EDA features but this is not verified using ECG features. Still, openness is better modelled using BVP and pupil features. Also, good results are achieved using all the biosignals together, which is in accordance with previous studies and features from EDA and ECG are more relevant. The features that best modelled openness are from the mouse interaction while answering online surveys, which relation was never reported before.

For the dimension of Conscientiousness, the predictive models that achieved good results were based on the pointer, EDA and BVP features. Individuals with high trait Conscientiousness think before they act, delay gratification, follow norms and rules, and plan, organize and prioritize tasks [162]. Individuals low in Conscientiousness may possess a more carefree orientation, be less punctual, and are less able to inhibit impulses and tend not to consider consequences [58]. Previous studies reported that this trait can be predicted by ECG and EDA [168, 243, 261], however our results do not support that features from ECG are predictive of conscientiousness.

The dimension of Extraversion achieved the second-best predictive models in a decision-making task. Individuals with high trait Extraversion are sociable, assertive and energetic. This behaviour is potentially modulated by the approach-oriented motivational system. Pilárik et al. [194] conclude that extraversion can predict the IGT score, however, the features of the IGT can not predict this trait in our study. About biosignals, the combination of all biosignals are predictive of extraversion, with a higher percentage for ECG and EDA features. Although previous authors predicted extraversion based on EDA and ECG [1, 168, 241, 283], only EDA and pupil accurately predicted extraversion. An association

between this trait and mouse movements velocity were also found by [35, 77, 217], which is supported by the good results of our predictive model.

For the dimension of Agreeableness, mouse and EDA features were not good predictors. Individuals with high trait Agreeableness are prosocial, altruistic, tender-minded, trustful, and modest, while those who are disagreeable are generally self-interested and tough-minded [58]. Despite this trait was well predicted by IGT features, the conclusion of [41] is not verified by the best features of our model. This was also verified with BVP features, that modelled well agreeableness. However, the features analysis are not in accordance with previous studies [241]. In agreement with [243], ECG features create an accurate model for our data. Although the model based only on EDA features does not predict this trait, in contrast to [168], the model with least error contemplates the biosignals, with more percentage of EDA features.

Although the dimension of Neuroticism is widely addressed in the literature, it is one of the scales with the worst model fitting in this thesis. Individuals with high trait Neuroticism are more sensitive to negative cues and characterized by emotional instability [58]. Many studies found Neuroticism associated with IGT performance [70, 120, 125], however, the features in which the predictive model is based are more related to reaction times. In relation to psychological changes, neuroticism was associated with responses of Heart Rate Variability (HRV) and Skin Conductance Response (SCR) [44, 62, 102, 168, 232, 243, 271] but this trait was not well predicted by these biosignals in this context. Yet, neuroticism is well modelled by BVP features from our data sets. Furthermore, the pointer interaction in online surveys can also accurately predict this trait.

Although we are limited to a few extreme subjects, for some dimensions the predictive model presented a good score, being one of the best five models for agreeableness (Mean Squared Error (MSE)=0.18) with biosignals features, openness (MSE=0.19) with pointer features, neuroticism (MSE=0.23) with BVP features, extraversion (MSE=0.29) with mouse features and openness (MSE=0.30) with BVP features.

The application of the two best models (openness and extraversion) based on mouse features in the NEO-FFI questionnaires with a sample of medical doctors are in accordance with the accuracy obtained in the evaluation phase of the models. The same models applied in a medical decision-making context did not achieve good results. Given that most of the features are micro-behaviours extracted from the interaction with a specific task, the approximation of each subscale in Multimorbidity Interaction Severity Index (MISI) to an item in the NEO-FFI questionnaire is probably the cause of the bad results. The cognitive effort for each subscale should be contemplated or each Disease–Disease, Drug–Disease, and Drug–Drug Interactions (DDIs) should be approximated to an item to achieve better results.

8.2 Contributions

The outcomes of this thesis are applied to a wide range of fields, from social sciences to engineering. These cover new data acquisition systems, development or improvement of decision-making tasks with concurrent data recording, signal processing of biosignals and Human-Computer Interaction (HCI) outputs and the machine learning models produced based on different sources. Some of these outcomes are already used in other research projects, which proves its potential for application. Following, each outcome of this thesis is described.

- Data acquisition:
 - *Latent*, a web browser extension that simultaneously captures information, particularly interaction, keyboard interaction, geolocation, browser tab screenshots, audio from microphone, video camera snapshots, document object model, and browser and tab settings is also a contributor for several fields like web usability studies or psychology research. Results published in [46].
- Decision-making tasks:
 - A template to be used in online surveys was generated, that integrates the pointer acquisition system. Furthermore, a new question type called *Array quad scale*, with four scales of answer options for each subquestion was built. These tools are being used in parallel research projects in the University Hospital of Zurich.
 - The decision-making task was redesigned and the integration of the eye-tracking and pointer acquisition was set up. This version of the task was used in research projects in the Department of Psychology of the University of Zurich.
 - MISI II. An online version of a tool to analyse medical decision-making with three hypothetical multimorbid patients. This tool may be used for medical research.
- Signal processing:
 - Processing tools developed for the pointer data analysis and a novel set of patterns are extracted from this interaction. These tools can be used for signal processing purposes or usability studies. Results published in [45].
 - The processing tools applied to physiological signals (ECG, EDA, BVP and pupil) are also outcomes of this thesis. A set of features related to the decision-making task are also developed. These tools can be used for signal processing purposes or psychology research.

- Machine learning:
 - Machine learning models for each personality trait are generated. Each personality trait is modelled individually by each input of human behaviour (pointer, decision-making task, decision-making task pointer, ECG, EDA, BVP and pupil features) and by the physiological signals (combination of ECG, EDA, BVP and pupil). Five different set of features arise from feature selection, that are further combined by seven different models algorithms. The process of creating and evaluating the models can be further used by engineers. The models can be applied to psychology research.
 - A model to detect uncertainty in items while answering a questionnaire in an online survey. This model can be applied in psychology or medical research. Results published in [72].

8.2.1 List of publications

8.2.1.1 Journal Papers

- *Latent: A Flexible Data Collection Tool to Research Human Behavior in the Context of Web Navigation.*
Cepeda, C., Tonet, R., Osorio, D. N., Silva, H. P., Battegay, E., Cheetham, M., & Gamboa, H.
 IEEE Access 2019

8.2.1.2 Pending Journal Papers

- *Usability of network-graph based visualization of drug-drug interactions for decision making in complex patients.* (in preparation)
 Roininen, S. M., **Cepeda, C.**, Tarcak, K., Cheetham, M.
- *Knowledge extraction from pointer movements and its application to detect uncertainty.* (submitted)
Cepeda C., Dias, M.C., Rindlisbacher, D., Cheetham, M., & Gamboa, H.
 Helyion

8.2.1.3 Conference Proceedings

- *Eye-pointer Coordination in a Decision-Making Task under Uncertainty* (submitted)
Cepeda C., Dias, M.C., Rindlisbacher, D., Cheetham, M., & Gamboa, H.
 BIOSTEC 2020 - 13th International Joint Conference on Biomedical Engineering Systems and Technologies
 Valleta, Malta, February 2020
- *Predicting response uncertainty in online surveys: A proof of concept.*
 Dias, M. C., **Cepeda, C.**, Rindlisbacher, D., Battegay, E., Cheetham, M., & Gamboa,

H.

BIOSTEC 2019 - 12th International Joint Conference on Biomedical Engineering Systems and Technologies

Prague, February 2019

- *Mouse tracking measures and movement patterns with application for online surveys.*
Cepeda, C., Rodrigues, J., Dias, M. C., Oliveira, D., Rindlisbacher, D., Cheetham, M., & Gamboa, H.
CD-MAKE 2018: International Cross Domain Conference for Machine Learning & Knowledge Extraction
Hamburg, Germany, August 27-30, 2018
- *Automated Detection of Mind Wandering: A Mobile Application.*
Cheetham, Marcus, **Cátia Cepeda**, and Hugo Gamboa.
BIOSTEC 2016 - 9th International Joint Conference on Biomedical Engineering Systems and Technologies
Rome, Italy, February 21-23, 2016

8.2.1.4 Oral Communications

- *Personality Assessment using Biosignals and Human Computer Interaction applied to Medical Decision Making*, Poster presentation
Catia Cepeda
NOVA Science Day – 2º Encontro de Ciência da NOVA 2019
- *Identification of mouse tracking measures and movement patterns and its application for uncertainty response prediction in online surveys*, Seminar
Doctoral Program, FCT-UNL, Caparica, Portugal, 2019
- *Arousal when making decisions predicts Big Five: A machine learning approach*, Poster presentation
Catia Cepeda, Dina Rindlisbacher, Beatriz Esteves, Julian Schneider, Edouard Battegay, Lutz Jäncke, Hugo Gamboa, Marcus Cheetham
University Research Priority Program (URPP) Internal Conference 2017
- *Electrodermal activity and its application to personality*, Lecture
Tópicos Avançados de Engenharia Biomédica, FCT-UNL, Caparica, Portugal, 2017.
- *Inter-individual Differences in On-line Pointer Movement Behaviour and the Personality Tendency to Maximize*, Lecture
1st Nova Biomedical Engineering Workshop 2016

8.3 Application Scenarios

The purpose of this thesis is to apply the developed tools to medical decision-making support, but a variety of fields can be interested in the attained outputs of our work.

- Decision-making process analysis: The relation between medical decision-making and personality is not the only field of application in terms of decision-making. Another example of application is in learning platforms, in which the process of learning may be related and adapted according to the personality of the user;
- Survey analysis: With the modelling process trained in the context of an online survey, its use or adaptation to this context will be easier, especially in cases of questionnaires with 5-Likert scale;
- Psychology or medical research: These fields of research are probably one of the most promising to benefit from our personality models. They may use the models to for example evaluate healthy and non-healthy subjects or evaluate cognitive tasks;
- Web usability tests: The pointer movement analysis and extraction of patterns may provide information to improve user-experience in web sites. The research of different personality traits' preferences in terms of design and content with a further prediction of personality may be a major contribution in the field of HCI;
- Human resources: During the recruiting process, some technical tests during the job interviews are applied to know the interviewed personality, therefore the use of the developed personality models may be a contributor to this area.

8.4 Future Work

With the conclusion of this thesis, the limitations of the research done should be overcome in future. Furthermore, some new questions arise throughout this thesis, that require further research. Following, some ideas that should be explored in future are described.

8.4.1 Extend the research

To verify the feasibility of this approach, a larger study sample with greater variability in the scores of the personality traits is needed. Our present study was mainly based on a relatively homogeneous sample of University students and this may have generated relatively truncated data (i.e. with few extreme scores in the traits scales). The findings of this study are promising that with larger data sets and real medical decision-making contexts, personality will have improved accuracy.

8.4.2 Balance between interpretability and accuracy

The work developed generated hundreds of machine learning models. These were grouped by data set and personality trait, and selected the one with higher accuracy, independently of the inherent model algorithm. Sometimes, the interpretability of the results is complex and, instead of selecting the model based on its error, a threshold between the complexity of the model algorithm and the final accuracy should be taken into consideration, even if the accuracy is slightly worsened.

8.4.3 Support medical decision-making

Research that associate decision-making styles of experts physicians to personality traits should be performed, to then help and guide non-experienced physicians with the best strategy to solve multimorbidity cases, according to their personality.

8.4.4 Beyond personality

In the developed work, only personality traits, particularly Big-Five personalities, are assessed and always compared with questionnaires' results. Given that a personality trait is a stable characteristic of an individual that explains how an individual usually behaves, a long-term experiment should be performed to verify which measures of behaviour are truly related to the personality trait and if it is not only an influence of the state of the individual. The state is a temporary condition, related to the mood, and, therefore, experienced for a short period. The state answers to how the person feels at the moment, while the trait answers to who the person is.

The definition of personality has only recently reached a consensus among theorists and, even if the questionnaires have a good internal consistency, the responses could depend on the subjective interpretation of the questions. Taking this into consideration, one approach that may be followed is to use unsupervised machine learning methods [274] with clustering algorithms to group individuals in terms of human behaviour. The analysis of the features of each group by psychologists may generate some conclusions about the characteristics of individuals based on how they behave. In 2018, researchers developed an alternative approach to the identification of personality types, after concluding that most of the people are average in the scales of the big-five personality traits, as it happened in our results [96]. In [278], the authors also defended that computer-based judgements in personality are more effective than made by humans.

8.5 Future Implications

The daily use of technologies, whether by a computer, smartphone or smartwatch, confirms the applicability of personality recognition using human body responses. The pointer movements are continuously acquired while individuals use the computer, for

example during a working day, and, although it is more difficult to acquire biosignals, some smartwatches already acquire HRV and EDA (e.g. [160]), and wearable technologies are facing an exponential growth [95, 101].

However, this is personal data and caution should be given to how the acquisition is made and who has access to the data. In 2016 [128], Facebook data of up to 87 million people may have been improperly shared with a company, Cambridge Analytica. This was the trigger to develop comprehensive privacy policy laws. The General Data Protection Regulation 2016/679 (GDPR) was implemented in May of 2018 and it is a regulation in European Union law on data protection and privacy for all individual citizens of the European Union and the European Economic Area [94]. The GDPR aims primarily to give control to individuals over their personal data and to simplify the regulatory environment for international business by unifying the regulation within the European Union [94].

This regulation also has an impact on machine learning applications, that when making a decision, the models should be transparent, understandable and explainable [118]. Thus, research in explainable-AI would allow the possibility to understand how and why a machine decision has been made. The introduction of high-level context features, as we contemplated in this study, incorporate direct explanations into the predictive models which could have a strong impact in explainable-AI.

BIBLIOGRAPHY

- [1] M. K. Abadi, M. Kia, R. Subramanian, P. Avesani, and N. Sebe. “Decoding affect in videos employing the MEG brain signal.” In: *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition, FG 2013*. IEEE, Apr. 2013, pp. 1–6. ISBN: 9781467355452. DOI: 10.1109/FG.2013.6553809. URL: <http://ieeexplore.ieee.org/document/6553809/>.
- [2] M. K. Abadi, J. A. M. Correa, J. Wache, H. Yang, I. Patras, and N. Sebe. “Inference of personality traits and affect schedule by analysis of spontaneous reactions to affective videos.” In: *2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition, FG 2015*. IEEE, May 2015, pp. 1–8. ISBN: 9781479960262. DOI: 10.1109/FG.2015.7163100. URL: <http://ieeexplore.ieee.org/document/7163100/>.
- [3] U. R. Acharya, K. P. Joseph, N. Kannathal, C. M. Lim, and J. S. Suri. “Heart rate variability: A review.” In: *Medical and Biological Engineering and Computing* 44.12 (Dec. 2006), pp. 1031–1051. ISSN: 01400118. DOI: 10.1007/s11517-006-0119-0. URL: <http://www.ncbi.nlm.nih.gov/pubmed/17111118><http://link.springer.com/10.1007/s11517-006-0119-0>.
- [4] A. A. E. Ahmed and I. Traore. “A new biometric technology based on mouse dynamics.” In: *IEEE Transactions on Dependable and Secure Computing* 4.3 (July 2007), pp. 165–179. ISSN: 15455971. DOI: 10.1109/TDSC.2007.70207. URL: <http://ieeexplore.ieee.org/document/4288179/>.
- [5] D. M. Alexander, C. Trengove, P. Johnston, T. Cooper, J. P. August, and E. Gordon. “Separating individual skin conductance responses in a short interstimulus-interval paradigm.” In: *Journal of Neuroscience Methods* 146 (2005), pp. 116–123. DOI: 10.1016/j.jneumeth.2005.02.001.
- [6] A. A. Alian and K. H. Shelley. “Photoplethysmography.” In: *Best Practice and Research: Clinical Anaesthesiology* 28.4 (Dec. 2014), pp. 395–406. ISSN: 1532169X. DOI: 10.1016/j.bpa.2014.08.006. URL: <https://www.sciencedirect.com/science/article/pii/S1521689614000755>.
- [7] J. Allen. “Photoplethysmography and its application in clinical physiological measurement.” In: *Physiological Measurement* 28.3 (Mar. 2007), R1–R39. ISSN: 09673334. DOI: 10.1088/0967-3334/28/3/R01.

- [8] G. W. Allport. *Personality: a psychological interpretation*. Oxford, England: Holt, 1937, pp. xiv, 588–xiv, 588.
- [9] J. L. Andreassi. *Psychophysiology : human behavior and physiological response*. Lawrence Erlbaum, 2007, p. 538. ISBN: 9780805849516.
- [10] M. Annett. “A classification of hand preference by association analysis.” In: *Br. J. Psychol.* 61 (1970), pp. 303–321. DOI: 10.1111/j.2044-8295.1970.tb01248.x.
- [11] I. Arapakis and L. A. Leiva. “Predicting user engagement with direct displays using mouse cursor information.” In: *SIGIR 2016 - Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval*. New York, New York, USA: ACM Press, 2016, pp. 599–608. ISBN: 9781450342902. DOI: 10.1145/2911451.2911505. URL: <http://dl.acm.org/citation.cfm?doi=2911451.2911505>.
- [12] G. Areias, R. Paixão, and A. P. C. Figueira. “O Iowa Gambling Task: Uma revisão crítica.” In: *Psicologia: Teoria e Pesquisa* 29.2 (June 2013), pp. 201–210. ISSN: 01023772. DOI: 10.1590/S0102-37722013000200009. URL: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0102-37722013000200009&lng=pt&tlng=pt.
- [13] E. Arroyo, T. Selker, and W. Wei. “Usability tool for analysis of web designs using mouse tracks.” In: *Conference on Human Factors in Computing Systems - Proceedings*. New York, New York, USA: ACM Press, 2006, pp. 484–489. ISBN: 1595932984. DOI: 10.1145/1125451.1125557. URL: <http://dl.acm.org/citation.cfm?doi=1125451.1125557>.
- [14] R. Atterer, M. Wnuk, and A. Schmidt. “Knowing the user’s every move: User activity tracking for website usability evaluation and implicit interaction.” In: *Proceedings of the 15th International Conference on World Wide Web*. New York, New York, USA: ACM Press, 2006, pp. 203–212. ISBN: 1595933239. DOI: 10.1145/1135777.1135811. URL: <http://portal.acm.org/citation.cfm?doid=1135777.1135811>.
- [15] D. R. Bach, K. J. Friston, and R. J. Dolan. “An improved algorithm for model-based analysis of evoked skin conductance responses.” In: *Biological Psychology* 94.3 (Dec. 2013), pp. 490–497. ISSN: 03010511. DOI: 10.1016/j.biopsycho.2013.09.010.
- [16] Y. Bachrach, M. Kosinski, T. Graepel, P. Kohli, and D. Stillwell. “Personality and patterns of Facebook usage.” In: *Proceedings of the 4th Annual ACM Web Science Conference, WebSci’12*. 2012, pp. 24–32. ISBN: 9781450312288. DOI: 10.1145/2380718.2380722. URL: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.296.4676&rep=rep1&type=pdf><http://dl.acm.org/citation.cfm?doi=2380718.2380722>.

-
- [17] J. E. Ball and J. S. Breese. *Modeling and projecting emotion and personality from a computer user interface*. 2001. URL: <https://patents.google.com/patent/US6212502B1/en>.
- [18] B. W. Balleine. “The neural basis of choice and decision making.” In: *Journal of Neuroscience* 27.31 (Aug. 2007), pp. 8159–8160. ISSN: 02706474. DOI: 10.1523/JNEUROSCI.1939-07.2007. URL: <http://www.jneurosci.org/cgi/doi/10.1523/JNEUROSCI.1939-07.2007>.
- [19] F. S. Bao, X. Liu, and C. Zhang. “PyEEG: An open source python module for EEG/MEG feature extraction.” In: *Computational Intelligence and Neuroscience* (2011), pp. 1–7. ISSN: 16875265. DOI: 10.1155/2011/406391. URL: <http://www.ncbi.nlm.nih.gov/pubmed/21512582><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3070217><http://www.hindawi.com/journals/cin/2011/406391/>.
- [20] E. Battegay, M. Cheetham, B. M. Holzer, A. Nowak, D. Schmidt, and S. Rampini. “Multimorbidity management and the physician’s daily clinical dilemma.” In: *Internist* 58.4 (Apr. 2017), pp. 344–353. ISSN: 14321289. DOI: 10.1007/s00108-017-0200-9. URL: <http://link.springer.com/10.1007/s00108-017-0200-9>.
- [21] N. Bayram and M. Aydemir. “Decision-Making Styles and Personality Traits.” In: *Proceedings of the International Conference on Multiple Academic Disciplines, Vietnam 3* (2017).
- [22] A. Bechara, A. R. Damasio, H. Damasio, and S. W. Anderson. “Insensitivity to future consequences following damage to human prefrontal cortex.” In: *Cognition* 50 (1994), pp. 7–15. DOI: doi:10.1016/0010-0277(94)90018-3.
- [23] A. Bechara, H. Damasio, and A. R. Damasio. “Emotion, Decision Making and the Orbitofrontal Cortex.” In: *Cerebral Cortex* 10.3 (Mar. 2000), pp. 295–307. ISSN: 14602199. DOI: 10.1093/cercor/10.3.295. URL: <https://academic.oup.com/cercor/article-lookup/doi/10.1093/cercor/10.3.295>.
- [24] A. Bechara, H. Damasio, D. Tranel, and A. R. Damasio. “Deciding advantageously before knowing the advantageous strategy.” In: *Science* 275.5304 (Feb. 1997), pp. 1293–1295. ISSN: 00368075. DOI: 10.1126/science.275.5304.1293. URL: <http://www.sciencemag.org/cgi/doi/10.1126/science.275.5304.1293>.
- [25] M. Benedek and C. Kaernbach. “A continuous measure of phasic electrodermal activity.” In: *Journal of Neuroscience Methods* 190.1 (2010), pp. 80–91. ISSN: 01650270. DOI: 10.1016/j.jneumeth.2010.04.028. URL: <http://dx.doi.org/10.1016/j.jneumeth.2010.04.028>.

- [26] M. Benedek and C. Kaernbach. "Decomposition of skin conductance data by means of nonnegative deconvolution." In: *Psychophysiology* 47.4 (July 2010), pp. 647–658. ISSN: 00485772. DOI: 10.1111/j.1469-8986.2009.00972.x. URL: <http://www.ncbi.nlm.nih.gov/pubmed/20230512><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC2904901>.
- [27] Biosignalsplux. *Electrodermal Activity (EDA) Sensor Data Sheet Miniaturized form factor for minimally-intrusive application on the subjects*. Tech. rep. 2015, p. 3. URL: <http://biosignalsplux.com/http://bit.ly/1HGyYE5><http://bit.ly/1Gw9r1x><http://bit.ly/1JraXmy><http://www.plux.info/files/ftp/docs/PaperMedeTel-HG.pdf> fig. 1..
- [28] V. Bjorn, C. Soutar, K. Irsch, D. L. Guyton, A. M. Burrows, J. F. Cohn, R. A. Hicklin, A. Kumar, T. S. Mundra, A. Kumar, F. Min, J. Suo, S.-C. Zhu, Y.-h. Li, and M. Savvides. "Anatomy of Eyes." In: *Encyclopedia of Biometrics*. Boston, MA: Springer US, 2009, pp. 11–16. DOI: 10.1007/978-0-387-73003-5_{_}253. URL: http://www.springerlink.com/index/10.1007/978-0-387-73003-5_253.
- [29] M. Bolanos, H. Nazeran, and E. Haltiwanger. "Comparison of heart rate variability signal features derived from electrocardiography and photoplethysmography in healthy individuals." In: *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*. IEEE, Aug. 2006, pp. 4289–4294. ISBN: 1424400325. DOI: 10.1109/IEMBS.2006.260607. URL: <http://ieeexplore.ieee.org/document/4462749/>.
- [30] P Borkenau and F Ostendorf. *NEO-Fünf-Faktoren-Inventar (NEO-FFI) nach Costa und McCrae*. Göttingen: Hogrefe, 1993, pp. 5–10.
- [31] W. Boucsein. *Electrodermal activity: Second edition*. Vol. 9781461411. Boston, MA: Springer US, 2012, pp. 1–618. ISBN: 9781461411260. DOI: 10.1007/978-1-4614-1126-0. URL: <http://link.springer.com/10.1007/978-1-4614-1126-0>.
- [32] C. M. Boyd, J. Darer, C. Boult, L. P. Fried, L. Boult, and A. W. Wu. "Clinical practice guidelines and quality of care for older patients with multiple comorbid diseases: Implications for pay for performance." In: *Journal of the American Medical Association* 294.6 (Aug. 2005), pp. 716–724. ISSN: 00987484. DOI: 10.1001/jama.294.6.716. URL: <http://www.ncbi.nlm.nih.gov/pubmed/16091574><http://jama.jamanetwork.com/article.aspx?doi=10.1001/jama.294.6.716>.
- [33] M. M. Bradley, L. Miccoli, M. A. Escrig, and P. J. Lang. "The pupil as a measure of emotional arousal and autonomic activation." In: *Psychophysiology* 45.4 (July 2008), pp. 602–607. ISSN: 00485772. DOI: 10.1111/j.1469-8986.2008.00654.x. URL: <http://www.ncbi.nlm.nih.gov/pubmed/18282202><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3612940><http://doi.wiley.com/10.1111/j.1469-8986.2008.00654.x>.

- [34] M. Brand, E. C. Recknor, F. Grabenhorst, and A. Bechara. "Decisions under ambiguity and decisions under risk: Correlations with executive functions and comparisons of two different gambling tasks with implicit and explicit rules." In: *Journal of Clinical and Experimental Neuropsychology* 29.1 (Jan. 2007), pp. 86–99. ISSN: 13803395. DOI: 10.1080/13803390500507196. URL: <http://www.tandfonline.com/doi/abs/10.1080/13803390500507196>.
- [35] J. Brebner. "S-R compatibility and changes in RT with practice." In: *Acta Psychologica* 37.2 (Apr. 1973), pp. 93–106. ISSN: 00016918. DOI: 10.1016/0001-6918(73)90023-1. URL: <https://www.sciencedirect.com/science/article/pii/0001691873900231>.
- [36] Breiman L. "Machine Learning, 45(1), 5–32." In: *Statistics Department, University of California, Berkeley, CA 94720*. 45.1 (2001), pp. 5–32. ISSN: 0885-6125. DOI: 10.1023/A:1010933404324. URL: <http://link.springer.com/10.1023/A:1010933404324>.
- [37] E. Bressert. *SciPy and NumPy*. O'Reilly Media, 2013. ISBN: 0636920020219.
- [38] G. Brighetti and C. Lucarelli. "Gender differences in attitudes towards risk and ambiguity: When psycho-physiological measurements contradict sex-based stereotypes." In: *International Journal of Entrepreneurship and Small Business* 24.1 (2015), pp. 62–82. ISSN: 17418054. DOI: 10.1504/IJESB.2015.066153. URL: <http://www.inderscience.com/link.php?id=66153>.
- [39] A. M. Brouwer, M. A. Hogervorst, M. Holewijn, and J. B. F. van Erp. "Evidence for effects of task difficulty but not learning on neurophysiological variables associated with effort." In: *International Journal of Psychophysiology* 93.2 (2014), pp. 242–252. ISSN: 18727697. DOI: 10.1016/j.ijpsycho.2014.05.004. URL: <http://dx.doi.org/10.1016/j.ijpsycho.2014.05.004>.
- [40] M. T. Buelow and J. A. Suhr. "Personality characteristics and state mood influence individual deck selections on the Iowa Gambling Task." In: *Personality and Individual Differences* 54.5 (Apr. 2013), pp. 593–597. ISSN: 01918869. DOI: 10.1016/j.paid.2012.11.019. URL: <https://www.sciencedirect.com/science/article/abs/pii/S0191886912005612>.
- [41] K. A. Byrne, C. D. Silasi-Mansat, and D. A. Worthy. "Who chokes under pressure? The Big Five personality traits and decision-making under pressure." In: *Personality and Individual Differences* 74 (Feb. 2015), pp. 22–28. ISSN: 0191-8869. DOI: 10.1016/J.PAID.2014.10.009. URL: <https://www.sciencedirect.com/science/article/pii/S0191886914005595>.
- [42] J. T. Cacioppo, L. G. Tassinary, and G. Berntson, eds. *Handbook of Psychophysiology*. Cambridge: Cambridge University Press, 2007. ISBN: 9780511546396. DOI: 10.1017/cbo9780511546396. URL: <http://ebooks.cambridge.org/ref/id/CB09780511546396>.

- [43] C. Camille, J. Martel-Pelletier, J. Sellam, J.-P. Pelletier, J.-P. Raynauld, and F. Roubille. *Journal of cardiology and therapy (Online)*. Vol. 2. 3. ACT Publishing Group Limited, June 2015, pp. 315–320. URL: <http://www.ghrnet.org/index.php/jct/article/view/1724/1986><http://www.ghrnet.org/index.php/jct/article/view/1203/1318>.
- [44] S. Carter and M. C. Smith Pasqualini. “Stronger autonomic response accompanies better learning: A test of Damasio’s somatic marker hypothesis.” In: *Cognition and Emotion* 18.7 (Nov. 2004), pp. 901–911. ISSN: 02699931. DOI: 10.1080/02699930341000338. URL: <https://www.tandfonline.com/doi/full/10.1080/02699930341000338>.
- [45] C. Cepeda, J. Rodrigues, M. C. Dias, D. Oliveira, D. Rindlisbacher, M. Cheetham, and H. Gamboa. “Mouse tracking measures and movement patterns with application for online surveys.” In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 11015 LNCS. s, 2018, pp. 28–42. ISBN: 9783319997391. DOI: 10.1007/978-3-319-99740-7_{_}3. URL: http://link.springer.com/10.1007/978-3-319-99740-7_3.
- [46] C. Cepeda, R. Tonet, D. N. Osorio, H. P. Silva, E. Battegay, M. Cheetham, and H. Gamboa. “Latent: A Flexible Data Collection Tool to Research Human Behavior in the Context of Web Navigation.” In: *IEEE Access* 7 (2019), pp. 77659–77673. ISSN: 21693536. DOI: 10.1109/ACCESS.2019.2916996. URL: <https://ieeexplore.ieee.org/document/8715366/>.
- [47] D. Cervone and L. A. Pervin. *Personality : theory and research*. Wiley, 2008, p. 645. ISBN: 9780471742418.
- [48] A. V. J. Challoner and C. A. Ramsay. “A photoelectric plethysmograph for the measurement of cutaneous blood flow.” In: *Physics in Medicine and Biology* 19.3 (May 1974), pp. 317–328. ISSN: 00319155. DOI: 10.1088/0031-9155/19/3/003. URL: <http://stacks.iop.org/0031-9155/19/i=3/a=003?key=crossref.6e06bf70ad11f395bc3f7481f848751e>.
- [49] T. Chaspari, A. Tsiartas, L. I. Stein, S. A. Cermak, and S. S. Narayanan. “Sparse representation of electrodermal activity with knowledge-driven dictionaries.” In: *IEEE Transactions on Biomedical Engineering* 62.3 (Mar. 2015), pp. 960–971. ISSN: 15582531. DOI: 10.1109/TBME.2014.2376960. URL: <http://www.ncbi.nlm.nih.gov/pubmed/25494494><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4362752>.
- [50] M. Cheetham, C. Cepeda, and H. Gamboa. “Automated Detection of Mind Wandering : A Mobile Application.” In: *Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2016)* (2016), pp. 198–205. DOI: 10.5220/0005702401980205.

- [51] J. Chen and J. Stallaert. “An economic analysis of online advertising using behavioral targeting.” In: *MIS Quarterly: Management Information Systems* 38.2 (June 2014), pp. 429–449. ISSN: 21629730. DOI: 10.25300/MISQ/2014/38.2.05. URL: <http://aisel.aisnet.org/misq/vol138/iss2/7>.
- [52] M. C. Chen, J. R. Anderson, and M. H. Sohn. “What can a mouse cursor tell us more?” In: *CHI '01 extended abstracts on Human factors in computing systems - CHI '01*. New York, New York, USA: ACM Press, 2001, p. 281. ISBN: 1581133405. DOI: 10.1145/634067.634234. URL: <http://portal.acm.org/citation.cfm?doid=634067.634234>.
- [53] D. Chudá and P. Krátky. “Usage of computer mouse characteristics for identification in web browsing.” In: *ACM International Conference Proceeding Series*. Vol. 883. New York, New York, USA: ACM Press, 2014, pp. 218–225. ISBN: 9781450327534. DOI: 10.1145/2659532.2659645. URL: <http://dl.acm.org/citation.cfm?doi=2659532.2659645>.
- [54] *Clicktale*. URL: <https://www.clicktale.com/> (visited on 04/25/2018).
- [55] F. G. Conrad, M. F. Schober, and T. Coiner. “Bringing features of human dialogue to web surveys.” In: *Applied Cognitive Psychology* 21.2 (Mar. 2007), pp. 165–187. ISSN: 08884080. DOI: 10.1002/acp.1335. URL: <http://doi.wiley.com/10.1002/acp.1335>.
- [56] J. K. Cooper. “Electrocardiography 100 years ago. Origins, pioneers, and contributors.” In: *The New England journal of medicine* 315.7 (Aug. 1986), pp. 461–4. ISSN: 0028-4793. DOI: 10.1056/NEJM198608143150721. URL: <http://www.ncbi.nlm.nih.gov/pubmed/3526152><http://www.nejm.org/doi/abs/10.1056/NEJM198608143150721>.
- [57] P. J. Corr and G. Matthews. *The Cambridge handbook of personality psychology*. Cambridge University Press, 2009, p. 850. ISBN: 9780511596544. URL: <https://www.cambridge.org/core/books/cambridge-handbook-of-personality-psychology/8E0820BD8B627FB17B009A34E81A5DEB>.
- [58] P. T. Costa. “Four ways five factors are basic.” In: *Personality and Individual Differences* 13.6 (June 1992), pp. 653–665. ISSN: 0191-8869. DOI: 10.1016/0191-8869(92)90236-I. URL: <https://www.sciencedirect.com/science/article/pii/019188699290236I>.
- [59] *Crazy Egg Website Optimization | Heatmaps & A/B Testing*. URL: <https://www.crazyegg.com/> (visited on 11/28/2018).
- [60] L. J. Cronbach. “Coefficient alpha and the internal structure of tests.” In: *Psychometrika* 16.3 (Sept. 1951), pp. 297–334. ISSN: 00333123. DOI: 10.1007/BF02310555. URL: <http://link.springer.com/10.1007/BF02310555>.

- [61] E. A. Crone, I. Vendel, and M. W. van der Molen. "Decision-making in disinhibited adolescents and adults: Insensitivity to future consequences or driven by immediate reward?" In: *Personality and Individual Differences* 35.7 (Nov. 2003), pp. 1625–1641. ISSN: 01918869. DOI: 10.1016/S0191-8869(02)00386-0. URL: <https://www.sciencedirect.com/science/article/pii/S0191886902003860>.
- [62] E. A. Crone, R. J. Somsen, B. Van Beek, and M. W. Van Der Molen. "Heart rate and skin conductance analysis of antecedents and consequences of decision making." In: *Psychophysiology* 41.4 (July 2004), pp. 531–540. ISSN: 00485772. DOI: 10.1111/j.1469-8986.2004.00197.x. URL: <http://www.ncbi.nlm.nih.gov/pubmed/15189476><http://doi.wiley.com/10.1111/j.1469-8986.2004.00197.x>.
- [63] A. R. Damasio. *Descartes' error : emotion, reason, and the human brain*. New York: Vintage Publishing, 1994, p. 312. ISBN: 014303622X.
- [64] R. B. Daroff. "The Pupil: Anatomy, Physiology, and Clinical Applications, Vols. I and II." In: *Neurology* 43.9 (1993), pp. 1868–1868. ISSN: 0028-3878. DOI: 10.1212/wnl.43.9.1868. URL: https://books.google.pt/books/about/The_Pupil.html?id=LoaXtwAACAAJ&redir_esc=y.
- [65] C. W. Darrow. "Neural mechanisms controlling the palmar galvanic skin reflex and palmar sweating: A consideration of available literature." In: *Archives of Neurology And Psychiatry* 37.3 (Mar. 1937), pp. 641–663. DOI: 10.1001/archneurpsyc.1937.02260150171011. URL: <http://archneurpsyc.jamanetwork.com/article.aspx?doi=10.1001/archneurpsyc.1937.02260150171011>.
- [66] J. DaVanzo. *Preparing for an Aging World*. Washington, D.C.: National Academies Press, June 2018. ISBN: 978-0-309-07421-6. DOI: 10.7249/rb5058. URL: <http://www.nap.edu/catalog/10120>.
- [67] W. B. De Bruin, A. M. Parker, and B. Fischhoff. "Individual differences in adult decision-making competence." In: *Journal of Personality and Social Psychology* 92.5 (May 2007), pp. 938–956. ISSN: 00223514. DOI: 10.1037/0022-3514.92.5.938. URL: <http://www.ncbi.nlm.nih.gov/pubmed/17484614><http://doi.apa.org/getdoi.cfm?doi=10.1037/0022-3514.92.5.938>.
- [68] V. De Pascalis, E. Strippoli, P. Riccardi, and F. Vergari. "Personality, event-related potential (ERP) and heart rate (HR) in emotional word processing." In: *Personality and Individual Differences* 36.4 (Mar. 2004), pp. 873–891. ISSN: 01918869. DOI: 10.1016/S0191-8869(03)00159-4. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0191886903001594>.
- [69] M. De Vries, R. W. Holland, and C. L. Witteman. "In the winning mood: Affect in the Iowa gambling task." In: *Judgment and Decision Making* 3.1 (2008), pp. 42–50. ISSN: 19302975. URL: <https://pdfs.semanticscholar.org/1aaf/1716ead9c3abd9cde1dc278f36db5591ee0c.pdf>.

- [70] N. L. Denburg, J. A. Weller, T. H. Yamada, D. M. Shivapour, A. R. Kaup, A Laloggia, C. A. Cole, D. Tranel, and A Bechara. "Poor decision making among older adults is related to elevated levels of neuroticism." In: *Annals of Behavioral Medicine* 37.2 (2009), pp. 164–172. ISSN: 08836612. DOI: 10.1007/s12160-009-9094-7. URL: <https://link.springer.com/content/pdf/10.1007%2Fs12160-009-9094-7.pdf>.
- [71] J. Deuel, R Moos, T Mehra, D. Schaer, M Cheetham, and E. Battegay. *Poster presentation at the Swiss Society of General Internal Medicine (SSGIM)*. Basel, Switzerland, 2016.
- [72] M. C. Dias, C. Cepeda, D. Rindlisbacher, E. Battegay, M. Cheetham, and H. Gamboa. "Predicting response uncertainty in online surveys: A proof of concept." In: *BIOSIGNALS 2019 - 12th International Conference on Bio-Inspired Systems and Signal Processing, Proceedings; Part of 12th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2019*. SCITEPRESS - Science and Technology Publications, 2019, pp. 155–162. ISBN: 9789897583537. DOI: 10.5220/0007381801550162. URL: <http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220/0007381801550162>.
- [73] A. Dillon and C. Watson. "User analysis in HCI - The historical lessons from individual differences research." In: *International Journal of Human Computer Studies* 45.6 (Dec. 1996), pp. 619–637. ISSN: 10715819. DOI: 10.1006/ijhc.1996.0071. URL: <https://www.sciencedirect.com/science/article/pii/S107158199600713>.
- [74] A. Dix. *Human-computer interaction*. Pearson/Prentice-Hall, 2004, p. 834. ISBN: 9780130461094.
- [75] S. Djasasbi, B. Tulu, E. Loiacono, and J. Whitefleet-Smith. "Can a Reasonable Time Limit Improve the Effective Usage of a Computerized Decision Aid?" In: *Communications of the Association for Information Systems* 23.22 (2008), pp. 393–408. ISSN: 15293181. DOI: 10.17705/1cais.02322. URL: <http://digitalcommons.wpi.edu/uxdmr1-pubshhttp://digitalcommons.wpi.edu/uxdmr1-pubs/27http://aisel.aisnet.org/cais/vol23/iss1/22>.
- [76] R. C. Dorf. "The Engineering handbook." In: *Choice Reviews Online* 42.06 (2005), pp. 42–3442. ISSN: 0009-4978. DOI: 10.5860/choice.42-3442.
- [77] C. Doucet and R. M. Stelmack. "Movement time differentiates extraverts from introverts." In: *Personality and Individual Differences* 23.5 (1997), pp. 775–786. ISSN: 01918869. DOI: 10.1016/S0191-8869(97)00104-9. URL: <https://www.sciencedirect.com/science/article/pii/S0191886997001049>.
- [78] B. D. Dunn, T. Dalgleish, and A. D. Lawrence. "The somatic marker hypothesis: A critical evaluation." In: *Neuroscience and Biobehavioral Reviews* 30.2 (2006), pp. 239–271. ISSN: 01497634. DOI: 10.1016/j.neubiorev.2005.07.001.

BIBLIOGRAPHY

- [79] D. Dunning, C. Heath, and J. M. Suls. “Flawed self-assessment implications for health, education, and the workplace.” In: *Psychological Science in the Public Interest, Supplement* 5.3 (Dec. 2004), pp. 69–106. ISSN: 15291006. DOI: 10.1111/j.1529-1006.2004.00018.x. URL: <http://www.ncbi.nlm.nih.gov/pubmed/26158995><http://journals.sagepub.com/doi/10.1111/j.1529-1006.2004.00018.x>.
- [80] *Electrocardiography (ECG) Sensor Data Sheet*. Tech. rep. 2017. URL: <http://biosignalsplux.com/>.
- [81] M. Elgendi. “On the Analysis of Fingertip Photoplethysmogram Signals.” In: *Current Cardiology Reviews* 8.1 (Feb. 2012), pp. 14–25. ISSN: 1573403X. DOI: 10.2174/157340312801215782. URL: <http://www.ncbi.nlm.nih.gov/pubmed/22845812><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3394104>.
- [82] J. D. Enderle and J. D. Bronzino. *Introduction to biomedical engineering*. Elsevier/Academic Press, 2012, p. 1252. ISBN: 9780123749796.
- [83] G. S. Everly and J. M. Lating. *A Clinical Guide to the Treatment of the Human Stress Response*. New York, NY: Springer New York, 2019. ISBN: 978-1-4614-5537-0. DOI: 10.1007/978-1-4939-9098-6. URL: <http://link.springer.com/10.1007/978-1-4614-5538-7>.
- [84] L. M. Fabbri, C. Boyd, P. Boschetto, K. F. Rabe, A. S. Buist, B. Yawn, B. Leff, D. M. Kent, and H. J. Schünemann. “How to integrate multiple comorbidities in guideline development: Article 10 in integrating and coordinating efforts in COPD guideline development. An official ATS/ERS workshop report.” In: *Proceedings of the American Thoracic Society*. Vol. 9. 5. Dec. 2012, pp. 274–281. DOI: 10.1513/pats.201208-063ST. URL: <http://www.ncbi.nlm.nih.gov/pubmed/23256171>.
- [85] R. Feinberg and E. Podolak. “Latency of pupillary reflex to light stimulation and its relationship to aging.” In: *Behavior, aging and the nervous system* (1965), pp. 326–339. ISSN: 1552-5783. DOI: 10.1167/iovs.02-0468. URL: <https://www.worldcat.org/title/latency-of-pupillary-reflex-to-light-stimulation-and-its-relationship-to-aging/oclc/84657376><http://iovs.arvojournals.org/article.aspx?doi=10.1167/iovs.02-0468>.
- [86] J. Feist and G. J. Feist. *Theories of personality*. McGraw Hill Higher Education, 2009. ISBN: 0073382701.
- [87] P. M. Fitts. “The information capacity of the human motor system in controlling the amplitude of movement.” In: *Journal of Experimental Psychology* 47.6 (1954), pp. 381–391. ISSN: 00221015. DOI: 10.1037/h0055392. URL: <http://doi.apa.org/getdoi.cfm?doi=10.1037/h0055392>.

- [88] I. H. A. Franken and P. Muris. “Individual differences in reward sensitivity are related to food craving and relative body weight in healthy women.” In: *Appetite* 45.2 (Oct. 2005), pp. 198–201. ISSN: 01956663. DOI: 10.1016/j.appet.2005.04.004. URL: <http://www.ncbi.nlm.nih.gov/pubmed/15949869><http://linkinghub.elsevier.com/retrieve/pii/S0195666305000425>.
- [89] L. W. Freedman, A. S. Scerbo, M. E. Dawson, A. Raine, W. O. McClure, and P. H. Venables. “The relationship of sweat gland count to electrodermal activity.” In: *Psychophysiology* 31.2 (1994), pp. 196–200.
- [90] J. H. Friedman. “Greedy function approximation: A gradient boosting machine.” In: *The Annals of Statistics* 29.5 (Oct. 2001), pp. 1189–1232. ISSN: 0090-5364. DOI: 10.1214/aos/1013203451. URL: <http://projecteuclid.org/euclid.aos/1013203451>.
- [91] H. Gamboa and A. Fred. “A behavioral biometric system based on human-computer interaction.” In: *Biometric Technology for Human Identification*. Ed. by A. K. Jain and N. K. Ratha. Vol. 5404. International Society for Optics and Photonics, Aug. 2004, pp. 381–392. DOI: 10.1117/12.542625. URL: <http://proceedings.spiedigitallibrary.org/proceeding.aspx?articleid=843484>.
- [92] H. F. S. Gamboa. “Multi-modal behavioral biometrics based on HCI and electrophysiology.” Doctoral dissertation. INSTITUTO SUPERIOR TECNICO, 2008, pp. 1–216. DOI: 10.1080/07924259.2010.9652324. URL: <http://www.lx.it.pt/~afred/pub/thesisHugoGamboa.pdf>.
- [93] D. Gassmann, M. Cheetham, K. Siebenhuener, B. M. Holzer, C. Meindl-Fridez, F. F. Hildenbrand, V. Virgini, M. Martin, and E. Battegay. “The multimorbidity interaction severity index (MISI) A proof of concept study.” In: *Medicine (United States)* 96.8 (Feb. 2017), e6144. ISSN: 15365964. DOI: 10.1097/MD.00000000000006144. URL: <http://insights.ovid.com/crossref?an=00005792-201702240-00014>.
- [94] *General Data Protection Regulation (GDPR) – Official Legal Text*. URL: <https://gdpr-info.eu/> (visited on 09/04/2019).
- [95] K. Georgiou, A. V. Larentzakis, N. N. Khamis, G. I. Alsuhaibani, Y. A. Alaska, and E. J. Giallafos. “Can Wearable Devices Accurately Measure Heart Rate Variability? A Systematic Review.” In: *Folia Medica I 2018 I* 60.1 (2018), pp. 7–20. DOI: 10.2478/foimed-2018-0012. URL: <https://www.degruyter.com/downloadpdf/j/foimed.2017.60.issue-1/foimed-2018-0012/foimed-2018-0012.pdf>.
- [96] M. Gerlach, B. Farb, W. Revelle, and L. A. Nunes Amaral. “A robust data-driven approach identifies four personality types across four large data sets.” In: *Nature Human Behaviour* 2.10 (Oct. 2018), pp. 735–742. ISSN: 2397-3374. DOI: 10.1038/s41562-018-0419-z. URL: <http://www.nature.com/articles/s41562-018-0419-z>.

BIBLIOGRAPHY

- [97] P. Geurts, D. Ernst, and L. Wehenkel. “Extremely randomized trees.” In: *Machine Learning* 63.1 (2006), pp. 3–42. ISSN: 0885-6125. DOI: 10.1007/s10994-006-6226-1. URL: <http://link.springer.com/10.1007/s10994-006-6226-1>.
- [98] B. O. Gilbert. “Physiological and nonverbal correlates of extraversion, neuroticism, and psychoticism during active and passive coping.” In: *Personality and Individual Differences* 12.12 (Jan. 1991), pp. 1325–1331. ISSN: 01918869. DOI: 10.1016/0191-8869(91)90208-S. URL: <https://www.sciencedirect.com/science/article/abs/pii/019188699190208S>.
- [99] C. Gilbert. “The Clinical Handbook of Biofeedback: A Step-by-Step Guide for Training and Practice with Mindfulness.” In: *Biofeedback* 42.3 (2014), pp. 130–132. ISSN: 1081-5937. DOI: 10.5298/1081-5937-42.3.05.
- [100] J. Golbeck, C. Robles, and K. Turner. “Predicting personality with social media.” In: *Conference on Human Factors in Computing Systems - Proceedings*. New York, New York, USA: ACM Press, 2011, pp. 253–262. ISBN: 9781450302289. DOI: 10.1145/1979742.1979614. URL: http://portal.acm.org/citation.cfm?doi_d=1979742.1979614.
- [101] C. Gonçalves, A. Ferreira da Silva, J. Gomes, and R. Simoes. “Wearable E-Textile Technologies: A Review on Sensors, Actuators and Control Elements.” In: *Inventions* 3.1 (Mar. 2018), p. 14. ISSN: 2411-5134. DOI: 10.3390/inventions3010014. URL: <http://www.mdpi.com/2411-5134/3/1/14>.
- [102] A. E. Goudriaan, J. Oosterlaan, E. de Beurs, and W. van den Brink. “Psychophysiological determinants and concomitants of deficient decision making in pathological gamblers.” In: *Drug and Alcohol Dependence* 84.3 (Oct. 2006), pp. 231–239. ISSN: 03768716. DOI: 10.1016/j.drugalcdep.2006.02.007. URL: <http://www.ncbi.nlm.nih.gov/pubmed/16574343><https://linkinghub.elsevier.com/retrieve/pii/S0376871606000664>.
- [103] A. Greco, G. Valenza, A. Lanata, E. P. Scilingo, and L. Citi. “CvxEDA: A convex optimization approach to electrodermal activity processing.” In: *IEEE Transactions on Biomedical Engineering* 63.4 (Apr. 2016), pp. 797–804. ISSN: 15582531. DOI: 10.1109/TBME.2015.2474131. URL: <http://www.ncbi.nlm.nih.gov/pubmed/26336110><http://ieeexplore.ieee.org/document/7229284/>.
- [104] B. S. Greenbaum. *Biological and Medical Physics, Biomedical Engineering*. Springer, 2012.
- [105] E. A. Griffin. *Interact System Model of Decision Emergence of B. Aubrey Fisher*. 1st. New York: A first look at communication theory, 1991, pp. 253–262. ISBN: 0070227780. URL: <http://www.afirstlook.com/docs/intersys.pdf>.

- [106] G.S. Sawhney, D. R. Tobergte, and S. Curtis. *Fundamentals of Biomedical Engineering*. Vol. 53. 9. New Age International, 2013, pp. 1689–1699. ISBN: 9788578110796. DOI: 10.1017/CB09781107415324.004. URL: <https://www.goodreads.com/book/show/7365596-fundamentals-of-biomedical-engineering>.
- [107] S. Guillaume, F. Jollant, I. Jaussent, N. Lawrence, A. Malafosse, and P. Courtet. “Somatic markers and explicit knowledge are both involved in decision-making.” In: *Neuropsychologia* 47.10 (Aug. 2009), pp. 2120–2124. ISSN: 00283932. DOI: 10.1016/j.neuropsychologia.2009.04.003. URL: <http://www.ncbi.nlm.nih.gov/pubmed/19427005><https://linkinghub.elsevier.com/retrieve/pii/S0028393209001651>.
- [108] K. L. Guo. “DECIDE: A decision-making model for more effective decision making by health care managers.” In: *Health Care Manager* 27.2 (Apr. 2008), pp. 118–127. ISSN: 15255794. DOI: 10.1097/01.HCM.0000285046.27290.90. URL: <http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00126450-200804000-00005>.
- [109] I. K. Gutermann, V. Niggemeier, L. U. Zimmerli, B. M. Holzer, E. Battagay, and M. Scharl. “Gastrointestinal bleeding and anticoagulant or antiplatelet drugs: Systematic search for clinical practice guidelines.” In: *Medicine (United States)* 94.1 (Jan. 2015), e377. ISSN: 15365964. DOI: 10.1097/MD.0000000000000377. URL: <http://www.ncbi.nlm.nih.gov/pubmed/25569664><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4602853><http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005792-201501010-00030>.
- [110] W. Handouzi, C. Maaoui, A. Pruski, and A. Moussaoui. “Objective model assessment for short-term anxiety recognition from blood volume pulse signal.” In: *Biomedical Signal Processing and Control* 14.1 (Nov. 2014), pp. 217–227. ISSN: 17468108. DOI: 10.1016/j.bspc.2014.07.008. URL: <https://www.sciencedirect.com/science/article/abs/pii/S1746809414001141>.
- [111] M. Hayhoe and D. Ballard. “Eye movements in natural behavior.” In: *Trends in Cognitive Sciences* 9.4 (Apr. 2005), pp. 188–194. ISSN: 13646613. DOI: 10.1016/j.tics.2005.02.009. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1364661305000598>.
- [112] R. M. Heilman, L. G. Crişan, D. Houser, M. Miclea, and A. C. Miu. “Emotion regulation and decision making under risk and uncertainty.” In: *Emotion* 10.2 (2010), pp. 257–265. ISSN: 1931-1516. DOI: 10.1037/a0018489. URL: <http://doi.apa.org/getdoi.cfm?doi=10.1037/a0018489>.
- [113] L. Hejfel and I. Gál. “Heart rate variability analysis.” In: *Acta Physiologica Hungarica* 88.3-4 (Sept. 2001), pp. 219–230. ISSN: 0231424X. DOI: 10.1556/APhysiol

BIBLIOGRAPHY

- .88.2001.3-4.4. URL: <http://www.ncbi.nlm.nih.gov/pubmed/12162580><http://www.akademai.com/doi/abs/10.1556/APhysiol.88.2001.3-4.4>.
- [114] M. Hibbeln, J. L. Jenkins, C. Schneider, J. S. Valacich, and M. Weinmann. “How Is Your User Feeling? Inferring Emotion Through Human-Computer interaction Devices.” In: *MIS Quarterly* 41.1 (2017), pp. 1–21. ISSN: 02767783. DOI: 10.25300/misq/2017/41.1.01.
- [115] D. E. Hinkle, W. Wiersma, and S. G. Jurs. *Applied statistics for the behavioral sciences*. 5th ed. Houghton Mifflin, 2003, p. 756. ISBN: 0618124055.
- [116] J. M. Hinson, T. L. Jameson, and P. Whitney. “Somatic markers, working memory, and decision making.” In: *Cognitive, Affective and Behavioral Neuroscience* 2.4 (Dec. 2002), pp. 341–353. ISSN: 15307026. DOI: 10.3758/CABN.2.4.341. URL: <http://www.springerlink.com/index/10.3758/CABN.2.4.341>.
- [117] G. P. Hodgkinson, N. J. Bown, A. J. Maule, K. W. Glaister, and A. D. Pearman. “Breaking the frame: An analysis of strategic cognition and decision making under uncertainty.” In: *Strategic Management Journal* 20.10 (1999), pp. 977–985. ISSN: 01432095. DOI: 10.1002/(SICI)1097-0266(199910)20:10<977::AID-SMJ58>3.0.CO;2-X. URL: <http://www.jstor.org/stable/3094159>.
- [118] A. Holzinger, C. Biemann, C. S. Pattichis, and D. B. Kell. “What do we need to build explainable AI systems for the medical domain?” In: *ArXiv 2017* (Dec. 2017). URL: <http://arxiv.org/abs/1712.09923>.
- [119] J. van Honk, E. J. Hermans, P. Putman, B. Montagne, and D. Schutter. “Defective somatic markers in sub-clinical psychopathy.” In: *Neuroreport* 13.8 (June 2002), pp. 1025–7. ISSN: 0959-4965. URL: <http://www.ncbi.nlm.nih.gov/pubmed/12060801>.
- [120] C. J. Hooper, M. Luciana, D. Wahlstrom, H. M. Conklin, and R. S. Yarger. “Personality correlates of Iowa Gambling Task performance in healthy adolescents.” In: *Personality and Individual Differences* 44.3 (Feb. 2008), pp. 598–609. ISSN: 01918869. DOI: 10.1016/j.paid.2007.09.021. URL: <https://www.sciencedirect.com/science/article/pii/S0191886907003406>.
- [121] R. Horwitz, F. Kreuter, and F. Conrad. “Using Mouse Movements to Predict Web Survey Response Difficulty.” In: *Social Science Computer Review* 35.3 (June 2017), pp. 388–405. ISSN: 15528286. DOI: 10.1177/0894439315626360. URL: <http://journals.sagepub.com/doi/10.1177/0894439315626360>.
- [122] Hotjar. *Hotjar - Heatmaps, Visitor Recordings, Conversion Funnels, Form Analytics, Feedback Polls and Surveys in One Platform*. 2018. URL: https://www.hotjar.com/home?utm{_}expid=.Z6cvEiV7SFmTDSpI1b1J-A.1{\&}utm{_}referrer=https{\%}3A{\%}2F{\%}2Fwww.google.pt{\%}2Fhttps://www.hotjar.com/.

- [123] J. Huang, R. W. White, and S. Dumais. “No clicks, no problem: Using cursor movements to understand and improve search.” In: *Conference on Human Factors in Computing Systems - Proceedings*. 2011, pp. 1225–1234. ISBN: 9781450302289. DOI: 10.1145/1978942.1979125.
- [124] J. D. Hunter. “Matplotlib: A 2D Graphics Environment.” In: *Computing in Science & Engineering* 9 (2007), pp. 90–95.
- [125] S. Icelliglu and M. S. Ozden. “Personality Effect on Decision-Making Among Normal University Students and Comparing Gambling Task Performances of Normal University Students with a Group of Normal Adults.” In: *Procedia - Social and Behavioral Sciences* 46 (2012), pp. 1010–1014. ISSN: 18770428. DOI: 10.1016/j.sbspro.2012.05.240. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1877042812013699>.
- [126] I. Guyon and A. Elisseeff. “An introduction to variable and feature selection.” In: *Journal of Machine Learning Research* 3 (2003), pp. 1157–1182. ISSN: 15324435. URL: <http://jmlr.csail.mit.edu/papers/volume3/guyon03a/guyon03a.pdf>.
- [127] *Inspectlet - Session Recording, Website Heatmaps, Javascript A/B Testing, Error Logging, Form Analytics*. URL: <https://www.inspectlet.com/> (visited on 11/28/2018).
- [128] J. Isaak and M. J. Hanna. “User Data Privacy: Facebook, Cambridge Analytica, and Privacy Protection.” In: *Computer* 51.8 (Aug. 2018), pp. 56–59. ISSN: 0018-9162. DOI: 10.1109/MC.2018.3191268. URL: <https://ieeexplore.ieee.org/document/8436400/>.
- [129] D. S. Jalajas and R. Pullaro. “The Effect of Personality on Decision Making.” In: *Journal of Organizational Psychology* 18.5 (Dec. 2018). ISSN: 2158-3609. DOI: 10.33423/jop.v18i5.274. URL: <https://articlegateway.com/index.php/JOP/article/view/274>.
- [130] G. James, D. Witten, T. Hastie, and R. Tibshirani. *Intro Statistical Learning*. New York: Springer New York, 2013, p. 441. ISBN: 9781461471370. URL: <http://www-bcf.usc.edu/~gareth/ISL/ISLRFfirstPrinting.pdf>.
- [131] T. L. Jameson, J. M. Hinson, and P. Whitney. “Components of working memory and somatic markers in decision making.” In: *Psychonomic bulletin & review* 11.3 (June 2004), pp. 515–20. ISSN: 1069-9384. URL: <http://www.ncbi.nlm.nih.gov/pubmed/15376804>.
- [132] R. D. Jenkins and S. J. Gerred. *ECGs by example*. Elsevier/Churchill Livingstone, 2011, p. 227. ISBN: 9780702049064.
- [133] E. A. Juliusson. “Effects of gain and loss frame on escalation.” In: *Göteborg Psychological Reports* 33.4 (2003). URL: https://www.ipd.gu.se/digitalAssets/1286/1286065_gpr03_nr4.pdf.

- [134] A. A. Kamal, J. B. Harness, G. Irving, and A. J. Mearns. "Skin photoplethysmography - a review." In: *Computer Methods and Programs in Biomedicine* 28.4 (Apr. 1989), pp. 257–269. ISSN: 01692607. DOI: 10.1016/0169-2607(89)90159-4. URL: <https://www.sciencedirect.com/science/article/pii/0169260789901594>.
- [135] A. Kampouraki, G. Manis, and C. Nikou. "Heartbeat time series classification with support vector machines." In: *IEEE Transactions on Information Technology in Biomedicine*. Vol. 13. 4. July 2009, pp. 512–518. DOI: 10.1109/TITB.2008.2003323. URL: <http://ieeexplore.ieee.org/document/4588343/>.
- [136] T. Katerina and P. Nicolaos. "Mouse behavioral patterns and keystroke dynamics in End-User Development: What can they tell us about users' behavioral attributes?" In: *Computers in Human Behavior* 83 (2018), pp. 288–305. ISSN: 07475632. DOI: 10.1016/j.chb.2018.02.012. URL: <https://www.sciencedirect.com/science/article/pii/S0747563218300700>.
- [137] I. A. Khan, W.-P. Brinkman, N. Fine, and R. M. Hierons. "Measuring personality from keyboard and mouse use." In: *Proceedings of the 15th European conference on Cognitive ergonomics the ergonomics of cool interaction - ECCE '08*. 2008, p. 1. ISBN: 9781605583990. DOI: 10.1145/1473018.1473066.
- [138] J. Kim and E. André. "Emotion recognition based on physiological changes in music listening." In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 30.12 (Dec. 2008), pp. 2067–2083. ISSN: 01628828. DOI: 10.1109/TPAMI.2008.26. URL: <http://ieeexplore.ieee.org/document/4441720/>.
- [139] R. E. Klabunde. "Cardiovascular Physiology Concepts." In: Lippincott Williams & Wilkins/Wolters Kluwer, 2003, p. 243. ISBN: 1451113846. URL: https://books.google.pt/books/about/Cardiovascular_Physiology_Concepts.html?id=27ExgvGn0agC&redir_esc=yhttp://www.cvphysiology.com/index.html.
- [140] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras. "DEAP: A Dataset for Emotion Analysis using Physiological and Audiovisual Signals." In: *IEEE Transactions on Affective Computing* 3.1 (2012), pp. 18–31. URL: <http://www.eecs.qmul.ac.uk/mmv/datasets/deap/>.
- [141] K. Korjus, A. Uusberg, H. Uusberg, N. Kuldkepp, K. Kreegipuu, J. Allik, R. Vicente, and J. Aru. "Personality cannot be predicted from the power of resting state EEG." In: *Frontiers in Human Neuroscience* 9.FEB (2015), p. 63. ISSN: 16625161. DOI: 10.3389/fnhum.2015.00063.
- [142] M. Kosinski, Y. Bachrach, P. Kohli, D. Stillwell, and T. Graepel. "Manifestations of user personality in website choice and behaviour on online social networks." In: *Machine Learning* 95.3 (June 2014), pp. 357–380. ISSN: 15730565. DOI: 10.1007/s10994-013-5415-y. URL: <http://link.springer.com/10.1007/s10994-013-5415-y>.

- [143] P. J. Lang, M. M. Bradley, and B. N. Cuthbert. "Emotion , Motivation , and Anxiety : Brain Mechanisms and Psychophysiology." In: *Biol Psychiatry* 44.12 (1998), pp. 1248–1263.
- [144] M. Lauriola and I. P. Levin. "Personality traits and risky decision-making in a controlled experimental task: An exploratory study." In: *Personality and Individual Differences* 31.2 (July 2001), pp. 215–226. ISSN: 01918869. DOI: 10.1016/S0191-8869(00)00130-6. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0191886900001306>.
- [145] C. Lavín, R. S. Martín, and E. R. Jubal. "Pupil dilation signals uncertainty and surprise in a learning gambling task." In: *Frontiers in Behavioral Neuroscience* 7 (2014). ISSN: 16625153. DOI: 10.3389/fnbeh.2013.00218. URL: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3879532/>.
- [146] J. A. R. Lenman. "The Human Nervous System." In: *Journal of Neurology, Neurosurgery, and Psychiatry* 38.12 (1975), p. 1245. URL: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC492199/>.
- [147] H. S. Levin, H. M. Eisenberg, and A. L. Benton. *Frontal lobe function and dysfunction*. Oxford University Press, 1991, p. 427. ISBN: 0195062841. URL: <https://global.oup.com/academic/product/frontal-lobe-function-and-dysfunction-9780195062847?cc=pt&lang=en&http://books.google.com/?id=9b1ht00V0rwC&pg=PA19&lpg=PA19&dq=Jacobsen++prefrontal+ablation&q=Jacobsenprefrontalablation>.
- [148] N. S. Levitt, K. Steyn, J. Dave, and D. Bradshaw. "Chronic noncommunicable diseases and HIV-AIDS on a collision course: Relevance for health care delivery, particularly in low-resource settings - Insights from South Africa." In: *American Journal of Clinical Nutrition*. Vol. 94. 6. Dec. 2011, 1690S–1696S. DOI: 10.3945/ajcn.111.019075. URL: <http://www.ncbi.nlm.nih.gov/pubmed/22089433http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3226022http://academic.oup.com/ajcn/article/94/6/1690S/4598216>.
- [149] C. Li, J. Wan, and B. Wang. "Personality Prediction of Social Network Users." In: *Proceedings - 2017 16th International Symposium on Distributed Computing and Applications to Business, Engineering and Science, DCABES 2017*. Vol. 2018-Sept. IEEE, Oct. 2018, pp. 84–87. ISBN: 9781538621622. DOI: 10.1109/DCABES.2017.25. URL: <http://ieeexplore.ieee.org/document/8253041/>.
- [150] M. Li and B. L. Lu. "Emotion classification based on gamma-band EEG." In: *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*. IEEE, Sept. 2009, pp. 1323–1326. ISBN: 9781424432967. DOI: 10.1109/IEMBS.2009.5334139. URL: <http://ieeexplore.ieee.org/document/5334139/>.

BIBLIOGRAPHY

- [151] C. L. Lim, C. Rennie, R. J. Barry, H. Bahramali, I. Lazzaro, B. Manor, and E. Gordon. "Decomposing skin conductance into tonic and phasic components." In: *International Journal of Human Computer Studies* 25 (1997), pp. 97–109.
- [152] C. L. Lisetti and F. Nasoz. "Using noninvasive wearable computers to recognize human emotions from physiological signals." In: *Eurasip Journal on Applied Signal Processing* 2004.11 (Dec. 2004), pp. 1672–1687. ISSN: 11108657. DOI: 10.1155/S1110865704406192. URL: <https://asp-urasipjournals.springeropen.com/articles/10.1155/S1110865704406192>.
- [153] H. D. Luijks, M. J. Loeffen, A. L. Lagro-Janssen, C. Van Weel, P. L. Lucassen, and T. R. Schermer. "GPs' considerations in multimorbidity management: A qualitative study." In: *British Journal of General Practice* 62.600 (July 2012), e503–e510. ISSN: 09601643. DOI: 10.3399/bjgp12X652373. URL: <http://bjgp.org/lookup/doi/10.3399/bjgp12X652373>.
- [154] F. Mairesse, M. A. Walker, M. R. Mehl, and R. K. Moore. "Using Linguistic Cues for the Automatic Recognition of Personality in Conversation and Text." In: *Journal of Artificial Intelligence Research* 30 (2007), pp. 457–500. URL: <https://www.aaai.org/Papers/JAIR/Vol130/JAIR-3012.pdf>.
- [155] M. Malik, A. J. Camm, J. T. Bigger, G. Breithardt, S. Cerutti, R. J. Cohen, P. Coumel, E. L. Fallen, H. L. Kennedy, R. E. Kleiger, F. Lombardi, A. Malliani, A. J. Moss, J. N. Rottman, G. Schmidt, P. J. Schwartz, and D. H. Singer. "Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology." In: *European heart journal* 17.3 (Mar. 1996), pp. 354–81. ISSN: 0195-668X. URL: <http://www.ncbi.nlm.nih.gov/pubmed/8737210>.
- [156] J. Malmivuo and R. Plonsey. *Bioelectromagnetism: Principles and Applications of Bioelectric and Biomagnetic Fields*. Oxford University Press, Oct. 2012, pp. 1–506. ISBN: 9780199847839. DOI: 10.1093/acprof:oso/9780195058239.001.0001. URL: <http://www.oxfordscholarship.com/view/10.1093/acprof:oso/9780195058239.001.0001/acprof-9780195058239>.
- [157] L. Mann, R. Harmoni, C. Power, G. Beswick, and C. Ormond. "Effectiveness of the GOFER course in decision making for high school students." In: *Journal of Behavioral Decision Making* 1.3 (July 1988), pp. 159–168. ISSN: 10990771. DOI: 10.1002/bdm.3960010304. URL: <http://doi.wiley.com/10.1002/bdm.3960010304>.
- [158] A. Marengoni, S. Angleman, R. Melis, F. Mangialasche, A. Karp, A. Garmen, B. Meinow, and L. Fratiglioni. "Aging with multimorbidity: A systematic review of the literature." In: *Ageing Research Reviews* 10.4 (Sept. 2011), pp. 430–439. ISSN:

15681637. DOI: 10.1016/j.arr.2011.03.003. URL: <http://www.ncbi.nlm.nih.gov/pubmed/21402176>.
- [159] D. Markovikj, S. Gievska, M. Kosinski, and D. Stillwell. "Mining facebook data for predictive personality modeling." In: *AAAI Workshop - Technical Report*. Vol. WS-13-01. 2013, pp. 23–26. ISBN: 9781577356110.
- [160] G. Marques and R. Pitarma. "Smartwatch-Based Application for Enhanced Healthy Lifestyle in Indoor Environments." In: Springer, Cham, Nov. 2019, pp. 168–177. DOI: 10.1007/978-3-030-03302-6_{_}15. URL: http://link.springer.com/10.1007/978-3-030-03302-6_15.
- [161] C. Massey, S. TenBrook, C. Tatum, and S. Whittaker. "PIM and personality: What do our personal file systems say about us?" In: *Conference on Human Factors in Computing Systems - Proceedings*. New York, New York, USA: ACM Press, 2014, pp. 3695–3704. ISBN: 9781450324731. DOI: 10.1145/2556288.2557023. URL: <http://dl.acm.org/citation.cfm?doid=2556288.2557023>.
- [162] R. R. McCrae and P. T. Costa. *Personality in Adulthood*. New York: Guilford, 1990.
- [163] R. R. McCrae and P. T. Costa Jr. "A contemplated revision of the NEO Five-Factor Inventory." In: *Personality and Individual Differences* 36 (2004), pp. 587–596. DOI: 10.1016/S0191-8869(03)00118-1.
- [164] C. McKinstry, R. Dale, and M. J. Spivey. "Action dynamics reveal parallel competition in decision making." In: *Psychological Science* 19.1 (Jan. 2008), pp. 22–24. ISSN: 09567976. DOI: 10.1111/j.1467-9280.2008.02041.x. URL: <http://www.ncbi.nlm.nih.gov/pubmed/18181787><http://journals.sagepub.com/doi/10.1111/j.1467-9280.2008.02041.x>.
- [165] J Medeiros, R Martins, S Palma, H Gamboa, and M Reis. "Blood Volume Pulse peak detector with a double adaptive threshold." In: *Technology and Medical Sciences - TMSi 2010*. 2011, pp. 345–347. ISBN: 9780203816592. URL: https://www.academia.edu/3020508/Blood_Volume_Pulse_Peak_Detector_with_a_Double_Adaptive_Threshold.
- [166] H. L. Meiselman. *Emotion Measurement*. Woodhead Publishing, 2016, pp. 1–726. ISBN: 9780081005095. DOI: 10.1016/C2014-0-03427-2.
- [167] R. Millis. *Advances in Electrocardiograms - Clinical Applications*. Ed. by R. Millis. InTech, Jan. 2012. ISBN: 978-953-307-902-8. DOI: 10.5772/1761. URL: <http://www.intechopen.com/books/advances-in-electrocardiograms-clinical-applications>.
- [168] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras. "AMIGOS: A Dataset for Affect , Personality and Mood Research on Individuals and Groups." In: *IEEE Transactions on Affective Computing* (2017), pp. 1–14.

BIBLIOGRAPHY

- [169] A. Mirhaghi, M. Mirhaghi, A. Oshio, and S. Sarabian. "Systematic Review of the Personality Profile of Paramedics: Bringing Evidence into Emergency Medical Personnel Recruitment Policy." In: *Eurasian Journal of Emergency Medicine* 15.3 (Aug. 2016), pp. 144–149. ISSN: 21495807. DOI: 10.5152/eajem.2016.80299. URL: <http://www.akademikaciltip.com/sayilar/247/buyuk/144-149.pdf>.
- [170] S. M. Mohammad and S. Kiritchenko. "Using nuances of emotion to identify personality." In: *AAAI Workshop - Technical Report*. Vol. WS-13-01. Sept. 2013, pp. 27–30. ISBN: 9781577356110. URL: <http://arxiv.org/abs/1309.6352>.
- [171] *Mouseflow*. URL: https://mouseflow.com/?gclid=CjwKCAiAlvnfBRA1EiwAV0Eg fHnRX - MXU9pACopLxprF8J -- 146n1vUE0UmGrE9HxD1XmXx6U9N0WhoCGggQAvD{_ }BwE (visited on 11/28/2018).
- [172] M. M. Mukaka. "Statistics Corner : A guide to appropriate use of Correlation coefficient in medical research." In: *Malawi Medical Journal* 24.3 (2012), pp. 69–71.
- [173] C. Muth, M. van den Akker, J. W. Blom, C. D. Mallen, J. Rochon, F. G. Schellevis, A. Becker, M. Beyer, J. Gensichen, H. Kirchner, R. Perera, A. Prados-Torres, M. Scherer, U. Thiem, H. van den Bussche, and P. P. Glasziou. "The Ariadne principles: How to handle multimorbidity in primary care consultations." In: *BMC Medicine* 12.1 (Dec. 2014), p. 223. ISSN: 17417015. DOI: 10.1186/s12916-014-0223-1. URL: <http://bmcmmedicine.biomedcentral.com/articles/10.1186/s12916-014-0223-1>.
- [174] E. Neumann and R. Blanton. "The Early History of Electrodermal Research." In: *Psychophysiology* 6.4 (Jan. 1970), pp. 453–475. ISSN: 14698986. DOI: 10.1111/j.1469-8986.1970.tb01755.x. URL: <http://doi.wiley.com/10.1111/j.1469-8986.1970.tb01755.x>.
- [175] W. Ng. "Clarifying the relation between neuroticism and positive emotions." In: *Personality and Individual Differences* 47.1 (July 2009), pp. 69–72. ISSN: 01918869. DOI: 10.1016/j.paid.2009.01.049. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0191886909000749>.
- [176] N. Nicholson, E. Soane, M. Fenton-O’Creevy, and P. Willman. "Personality and domain-specific risk taking." In: *Journal of Risk Research* 8.2 (Mar. 2005), pp. 157–176. ISSN: 13669877. DOI: 10.1080/1366987032000123856. URL: <https://www.tandfonline.com/doi/full/10.1080/1366987032000123856>.
- [177] J. Oliver, R. Richard, and P. Lawrence. *Handbook of Personality : Theory and Research*. Guilford Publications, 2008, p. 2766. ISBN: 1606237381. URL: https://books.google.pt/books/about/Handbook_of_Personality_Third_Edition.html?id=8r4K1gerjcUC&redir_esc=y.

- [178] T. Oni, N. McGrath, R. BeLue, P. Roderick, S. Colagiuri, C. R. May, and N. S. Levitt. "Chronic diseases and multi-morbidity - A conceptual modification to the WHO ICCC model for countries in health transition." In: *BMC Public Health* 14.1 (Dec. 2014), p. 575. ISSN: 14712458. DOI: 10.1186/1471-2458-14-575. URL: <http://www.ncbi.nlm.nih.gov/pubmed/24912531><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4071801><http://bmcpublichealth.biomedcentral.com/articles/10.1186/1471-2458-14-575>.
- [179] W. H. Organization. *WHO | Global status report on noncommunicable diseases 2010*. Tech. rep. 2015. URL: http://www.who.int/nmh/publications/ncd{_}report2010/en/.
- [180] A. Ortigosa, R. M. Carro, and J. I. Quiroga. "Predicting user personality by mining social interactions in Facebook." In: *Journal of Computer and System Sciences*. Vol. 80. 1. Academic Press, Feb. 2014, pp. 57–71. DOI: 10.1016/j.jcss.2013.03.008. URL: <http://www.sciencedirect.com/science/article/pii/S00220001300072X>.
- [181] H. Oya, R. Adolphs, H. Kawasaki, A. Bechara, A. Damasio, and M. A. Howard. "Electrophysiological correlates of reward prediction error recorded in the human prefrontal cortex." In: *Proceedings of the National Academy of Sciences of the United States of America* 102.23 (June 2005), pp. 8351–8356. ISSN: 00278424. DOI: 10.1073/pnas.0500899102. URL: <http://www.ncbi.nlm.nih.gov/pubmed/15928095><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1149421><http://www.pnas.org/cgi/doi/10.1073/pnas.0500899102>.
- [182] R. Paixão and G. Areias. "Personality in decision making with the Iowa Gambling Task: An integrative review." In: *Psicologia: Teoria e Pesquisa* 33.0 (Nov. 2017), pp. 1–10. ISSN: 18063446. DOI: 10.1590/0102.3772e33415. URL: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0102-37722017000100413&lng=pt&tlng=pt.
- [183] J. Pan and J Willis. "A Real-Time QRS Detection Algorithm." In: *Engineer BME*-32.3 (Mar. 1985), pp. 230–236. ISSN: 0018-9294. DOI: 10.1109/TBME.1985.325532. URL: <http://ieeexplore.ieee.org/document/4122029/>.
- [184] H. A. Park. "An introduction to logistic regression: From basic concepts to interpretation with particular attention to nursing domain." In: *Journal of Korean Academy of Nursing* 43.2 (Apr. 2013), pp. 154–164. ISSN: 20937482. DOI: 10.4040/jkan.2013.43.2.154. URL: <http://www.ncbi.nlm.nih.gov/pubmed/23703593><http://synapse.koreamed.org/DOIx.php?id=10.4040/jkan.2013.43.2.154>.
- [185] L. Parks-Leduc, G. Feldman, and A. Bardi. "Personality Traits and Personal Values: A Meta-Analysis." In: *Personality and Social Psychology Review* 19.1 (Feb. 2015), pp. 3–29. ISSN: 10888683. DOI: 10.1177/1088868314538548. URL: <http://www>

BIBLIOGRAPHY

- .ncbi.nlm.nih.gov/pubmed/24963077<http://journals.sagepub.com/doi/10.1177/1088868314538548>.
- [186] D. L. Paulhus and S. Vazire. “The Self-Report Method.” In: *Handbook of Research Methods in Personality Psychology*. Ed. by R. Robins, R. C. Fraley, and R. F. Krueger. New York, NY: The Guilford Press., 2007, pp. 224–239. URL: <https://pdfs.semanticscholar.org/aaf2/09e53a0837621062126080263a89a38321d7.pdf>.
- [187] J. W. Payne, J. R. Bettman, and E. J. Johnson. “Adaptive Strategy Selection in Decision Making.” In: *Journal of Experimental Psychology: Learning, Memory, and Cognition* 14.3 (1988), pp. 534–552. ISSN: 02787393. DOI: 10.1037/0278-7393.14.3.534. URL: <http://doi.apa.org/getdoi.cfm?doi=10.1037/0278-7393.14.3.534>.
- [188] *PCL Output Files*. URL: https://www.neurobs.com/pres{_}docs/html/03{_}presentation/07{_}data{_}reporting/03{_}pcl{_}output{_}files.htm (visited on 04/09/2019).
- [189] F. Pedregosa, R. Weiss, and M. Brucher. “Scikit-learn : Machine Learning in Python.” In: *Journal of Machine Learning Research* 12 (2011), pp. 2825–2830.
- [190] D. H. Pelt, D. van der Linden, C. S. Dunkel, and M. P. Born. “The general factor of personality and job performance: Revisiting previous meta-analyses.” In: *International Journal of Selection and Assessment* 25.4 (Dec. 2017), pp. 333–346. ISSN: 14682389. DOI: 10.1111/ijsa.12188. URL: <http://doi.wiley.com/10.1111/ijsa.12188>.
- [191] E. Peper, R. Harvey, I.-M. Lin, H. Tylova, and D. Moss. “Is There More to Blood Volume Pulse Than Heart Rate Variability , Respiratory Sinus Arrhythmia , and Cardiorespiratory Synchrony ?” In: *Biofeedback* 35.2 (2007), pp. 54–61. ISSN: 10815937.
- [192] E. Peters and P. Slovic. “The springs of action: Affective and analytical information processing in choice.” In: *Personality and Social Psychology Bulletin* 26.12 (Dec. 2000), pp. 1465–1475. ISSN: 01461672. DOI: 10.1177/01461672002612002. URL: <http://journals.sagepub.com/doi/10.1177/01461672002612002>.
- [193] J. Pijanowski. “The Role of Learning Theory in Building Effective College Ethics Curricula.” In: *Journal of College and Character* 10.3 (2009). ISSN: 2194-587X. DOI: 10.2202/1940-1639.1088. URL: <http://www.tandfonline.com/action/journalInformation?journalCode=ujcc20>.
- [194] L. Pilárik and I. Sarmány-Schuller. “Personality predictors of decision-making of medical rescuers.” In: *Studia Psychologica* 53.2 (2011), pp. 175–184. ISSN: 00393320. URL: http://www.studiapsychologica.com/uploads/PILARIK_SP_02_vol.53_2011_pp.175-184.pdf.

- [195] A. Pimenta, D. Carneiro, P. Novais, and J. Neves. “Monitoring mental fatigue through the analysis of keyboard and mouse interaction patterns.” In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 8073 LNAI (2013), pp. 222–231. ISSN: 03029743. DOI: 10.1007/978-3-642-40846-5{_}23.
- [196] G. Piñeiro, J. P. Guerschman, S. Perelman, and J. Paruelo. “How to evaluate models: Observed vs. predicted or predicted vs. observed?” In: *Ecological Modelling* 216.3-4 (2008), pp. 316–322. ISSN: 0304-3800. DOI: 10.1016/J.ECOLMODEL.2008.05.006. URL: <http://www.sciencedirect.com/science/article/pii/S0304380008002305>.
- [197] Plux. *Blood Volume Pulse (BVP) Sensor Data Sheet*. 2015. URL: <http://biosignalsplux.com/>.
- [198] Plux. *Biosignalsplux | Wearable Body Sensing Platform*. 2017. URL: <https://www.biosignalsplux.com/en/software/apis> (visited on 04/11/2019).
- [199] PLUX. *Plux Wireless Biosignals*. 2018. URL: <https://www.plux.info/index.php/en/www.plux.info> (visited on 04/11/2019).
- [200] K. E. Pocius. “Personality factors in human-computer interaction: A review of the literature.” In: *Computers in Human Behavior* 7.3 (Jan. 1991), pp. 103–135. ISSN: 07475632. DOI: 10.1016/0747-5632(91)90002-I. URL: <https://www.sciencedirect.com/science/article/pii/074756329190002I>.
- [201] S. Poria, A. Gelbukh, B. Agarwal, E. Cambria, and N. Howard. “Common sense knowledge based personality recognition from text.” In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 8266 LNAI. PART 2. Springer, Berlin, Heidelberg, Nov. 2013, pp. 484–496. ISBN: 9783642451102. DOI: 10.1007/978-3-642-45111-9{_}42.
- [202] K. Preuschoff, B. M. Hart, and W. Einhäuser. “Pupil dilation signals surprise: Evidence for noradrenaline’s role in decision making.” In: *Frontiers in Neuroscience* 5.SEP (2011), pp. 1–12. ISSN: 16624548. DOI: 10.3389/fnins.2011.00115. URL: <http://www.ncbi.nlm.nih.gov/pubmed/21994487><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3183372>.
- [203] M. Pusara and C. E. Brodley. “User re-authentication via mouse movements.” In: *VizSEC/DMSEC ’04: Proceedings of the 2004 ACM Workshop on Visualization and Data Mining for Computer Security*. New York, New York, USA: ACM Press, 2004, pp. 1–8. ISBN: 1581139748. DOI: 10.1145/1029208.1029210. URL: <http://portal.acm.org/citation.cfm?doid=1029208.1029210>.

- [204] D. Quercia, M. Kosinski, D. Stillwell, and J. Crowcroft. "Our twitter profiles, our selves: Predicting personality with twitter." In: *Proceedings - 2011 IEEE International Conference on Privacy, Security, Risk and Trust and IEEE International Conference on Social Computing, PASSAT/SocialCom 2011*. IEEE, Oct. 2011, pp. 180–185. ISBN: 9780769545783. DOI: 10.1109/PASSAT/SocialCom.2011.26. URL: <http://ieeexplore.ieee.org/document/6113111/>.
- [205] H. M. Rahaman. "Personality and Decision Making Styles of University Students." In: *Journal of the Indian Academy of Applied Psychology* 40 (2014).
- [206] E. Rassin. "A psychological theory of indecisiveness." In: *Netherlands journal of psychology* 63.1 (Mar. 2007), pp. 1–11. ISSN: 1872-552X. DOI: 10.1007/bf03061056. URL: <http://link.springer.com/10.1007/BF03061056>.
- [207] K Rayner. "Eye movements in reading and information processing: 20 years of research." In: *Psychological bulletin* 124.3 (Nov. 1998), pp. 372–422. ISSN: 0033-2909. URL: <http://www.ncbi.nlm.nih.gov/pubmed/9849112>.
- [208] R Reavis and W. H. Overman. "Adult sex differences on a decision-making task previously shown to depend on the orbital prefrontal cortex." In: *Behavioral neuroscience* 115.1 (Feb. 2001), pp. 196–206. ISSN: 0735-7044. URL: <http://www.ncbi.nlm.nih.gov/pubmed/11256443>.
- [209] P. Refaeilzadeh, L. Tang, and H. Liu. "Cross-Validation." In: *Encyclopedia of Database Systems*. Ed. by L. LIU and M. T. ÖZSU. Boston, MA: Springer US, 2009, pp. 532–538. ISBN: 978-0-387-39940-9. DOI: 10.1007/978-0-387-39940-9_{_}565. URL: https://doi.org/10.1007/978-0-387-39940-9_565.
- [210] P. J. Rentfrow and S. D. Gosling. "The Do Re Mi's of Everyday Life: The Structure and Personality Correlates of Music Preferences." In: *Journal of Personality and Social Psychology* 84.6 (2003), pp. 1236–1256. ISSN: 00223514. DOI: 10.1037/0022-3514.84.6.1236. URL: <http://www.stat.ufl.edu/STA4702/Spring07/Rentfrow&Gosling.pdf><http://doi.apa.org/getdoi.cfm?doi=10.1037/0022-3514.84.6.1236>.
- [211] K. Revett, H. Jahankhani, S. T. de Magalhães, and H. M. D. Santos. "A Survey of User Authentication Based on Mouse Dynamics." In: Springer, Berlin, Heidelberg, 2008, pp. 210–219. ISBN: 978-3-540-69402-1. DOI: 10.1007/978-3-540-69403-8_{_}25.
- [212] K. Rodden and X. Fu. "Exploring how mouse movements relate to eye movements on web search results pages." In: *Special Interest Group on Information Retrieval Workshop on Web Information Seeking and Interaction*. 2007, pp. 29–32. DOI: 10.1080/02626667.2013.825722. URL: <http://www.rodten.org/kerry/publications/wisi07/http://www.australianscience.com.au/research/google/32735.pdf#page=33>.

- [213] J. D. Rodríguez, A. Pérez, and J. A. Lozano. “Sensitivity Analysis of k-Fold Cross Validation in Prediction Error Estimation.” In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 32.3 (Mar. 2010), pp. 569–575. ISSN: 01628828. DOI: 10.1109/TPAMI.2009.187. URL: <http://www.ncbi.nlm.nih.gov/pubmed/20075479><http://ieeexplore.ieee.org/document/5342427/>.
- [214] R. D. Rogers, A. M. Owen, H. C. Middleton, E. J. Williams, J. D. Pickard, B. J. Sahakian, and T. W. Robbins. “Choosing between Small , Likely Rewards and Large , Unlikely Rewards Activates Inferior and Orbital Prefrontal Cortex.” In: *The Journal of neuroscience : the official journal of the Society for Neuroscience* 20.19 (1999), pp. 9029–9038.
- [215] G van Rossum and Others. *pickle - Python object serialization*. 2009. URL: <https://docs.python.org/3/library/pickle.html><http://docs.python.org/library/pickle.html> (visited on 07/12/2019).
- [216] R. M. Ryckman. *Theories of personality*. Thomson/Wadsworth, 2008, p. 711. ISBN: 0495099082. URL: https://books.google.pt/books/about/Theories_of_Personality.html?id=_1mQhvUfYfWc&redir_esc=y.
- [217] B. Saati, M. Salem, and W.-P. Brinkman. “Towards customized user interface skins: investigating user personality and skin colour.” In: *Hci 2005* 2.1 (2005), pp. 86–93. URL: http://mmi.tudelft.nl/~willem-paul/WP_Papers_online_versie/Towards_customized_user_interface_skins.pdf.
- [218] A. P. Sanil. “Principles of Data Mining.” In: *Journal of the American Statistical Association* 98.461 (2003), pp. 252–253. ISSN: 0162-1459. DOI: 10.1198/jasa.2003.s257. URL: <https://mitpress.mit.edu/books/principles-data-mining>.
- [219] T. D. Satterthwaite, L. Green, J. Myerson, J. Parker, M. Ramaratnam, and R. L. Buckner. “Dissociable but inter-related systems of cognitive control and reward during decision making: Evidence from pupillometry and event-related fMRI.” In: *NeuroImage* 37.3 (Sept. 2007), pp. 1017–1031. ISSN: 10538119. DOI: 10.1016/j.neuroimage.2007.04.066. URL: <http://www.ncbi.nlm.nih.gov/pubmed/17632014><https://linkinghub.elsevier.com/retrieve/pii/S1053811907003424>.
- [220] H. Schlosberg. “Three dimensions of emotion.” In: *Psychological Review* 61.2 (1954), pp. 81–88. ISSN: 0033295X. DOI: 10.1037/h0054570. URL: <http://doi.apa.org/getdoi.cfm?doi=10.1037/h0054570>.
- [221] I. K. Schneider, F. van Harreveld, M. Rotteveel, S. Topolinski, J. van der Pligt, N. Schwarz, and S. L. Koole. “The path of ambivalence: tracing the pull of opposing evaluations using mouse trajectories.” In: *Frontiers in Psychology* 6 (2015), p. 996. ISSN: 1664-1078. DOI: 10.3389/fpsyg.2015.00996. URL: <http://www.ncbi.nlm.nih.gov/pubmed/26236267><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4505081>.

BIBLIOGRAPHY

- [222] A. C. Schütz, D. I. Braun, and K. R. Gegenfurtner. “Eye movements and perception: A selective review.” In: *Journal of Vision* 11.5 (Sept. 2011), pp. 1–30. ISSN: 15347362. DOI: 10.1167/11.5.1. URL: <http://jov.arvojournals.org/Article.aspx?doi=10.1167/11.5.9>.
- [223] N. Schwarz, B. Knauper, H.-J. Hippler, E. Noelle-Neumann, and L. Clark. “Rating Scales: Numeric Values May Change the Meaning of Scale Labels.” In: *Public Opinion Quarterly* 55.4 (1991), p. 570. ISSN: 0033362X. DOI: 10.1086/269282. URL: <https://academic.oup.com/poq/article-lookup/doi/10.1086/269282>.
- [224] *seaborn: statistical data visualization*. URL: <https://seaborn.pydata.org/> (visited on 10/08/2017).
- [225] A. Seelye, S. Hagler, N. Mattek, D. B. Howieson, K. Wild, H. H. Dodge, and J. A. Kaye. “Computer mouse movement patterns: A potential marker of mild cognitive impairment.” In: *Alzheimer’s and Dementia: Diagnosis, Assessment and Disease Monitoring* 1.4 (Dec. 2015), pp. 472–480. ISSN: 23528729. DOI: 10.1016/j.dadm.2015.09.006. URL: <https://www.sciencedirect.com/science/article/pii/S2352872915000792><http://linkinghub.elsevier.com/retrieve/pii/S2352872915000792>.
- [226] J. L. Semmlow. *Biosignal and Medical Image Processing*. CRC Press, 2008, p. 608. ISBN: 9781466567368. DOI: 10.1201/9780203024058. URL: <https://www.crcpress.com/Biosignal-and-Medical-Image-Processing/Semmlow-Griffel/p/book/9781466567368>.
- [227] C. Setz, B. Arnrich, J. Schumm, R. L. Marca, G. Troster, and U. Ehlert. “Discriminating Stress From Cognitive Load Using a Wearable EDA Device.” In: *IEEE Transactions on Information in Biomedicine*. Vol. 14. 2. 2010, pp. 410–417.
- [228] F. Shaffer and J. P. Ginsberg. “An Overview of Heart Rate Variability Metrics and Norms.” In: *Frontiers in Public Health* 5 (Sept. 2017), p. 258. ISSN: 2296-2565. DOI: 10.3389/fpubh.2017.00258. URL: <http://journal.frontiersin.org/article/10.3389/fpubh.2017.00258/full>.
- [229] L. A. Shalabi, Z. Shaaban, and B. Kasasbeh. “Data Mining: A Preprocessing Engine.” In: *Journal of Computer Science* 2.9 (2006), pp. 735–739. ISSN: 15493636. DOI: 10.3844/jcssp.2006.735.739. URL: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.121.2072&rep=rep1&type=pdf>.
- [230] C. R. Shalizi. *Advanced data analysis from an elementary point of view*. Cambridge University Press, 2013, p. 801. URL: <https://www.stat.cmu.edu/~cshalizi/ADAfaEPoV/ADAfaEPoV.pdf><http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.371.4613&rep=rep1&type=pdf>.

- [231] Z. Sharafi, Z. Soh, and Y. G. Guéhéneuc. “A systematic literature review on the usage of eye-tracking in software engineering.” In: *Information and Software Technology*. Vol. 67. Nov. 2015, pp. 79–107. DOI: 10.1016/j.infsof.2015.06.008. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0950584915001196>.
- [232] D. Shepherd, J. Mulgrew, and M. J. Hautus. “Exploring the autonomic correlates of personality.” In: *Autonomic Neuroscience: Basic and Clinical* 193 (Dec. 2015), pp. 127–131. ISSN: 18727484. DOI: 10.1016/j.autneu.2015.05.004. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1566070215000545>.
- [233] SickKids Staff. *Eye anatomy and function [Online image]*. 2011. URL: <http://www.aboutkidshealth.ca/En/HealthAZ/HealthandWellness/EyeandEarCare/Pages/Eye-Anatomy-and-Function.aspx> (visited on 04/16/2019).
- [234] B. Simonovic, E. J. Stupple, M. Gale, and D. Sheffield. “Stress and Risky Decision Making: Cognitive Reflection, Emotional Learning or Both.” In: *Journal of Behavioral Decision Making* 30.2 (Apr. 2017), pp. 658–665. ISSN: 10990771. DOI: 10.1002/bdm.1980. URL: <http://doi.wiley.com/10.1002/bdm.1980>.
- [235] SMI. *Begaze manual*. 2010. URL: https://psychologie.unibas.ch/fileadmin/user_upload/psychologie/Forschung/N-Lab/SMI_BeGaze_Manual.pdf.
- [236] F. Software, C. Project, and S. Support. “LimeSurvey - The Online Survey Tool.” In: *Online* (2009), pp. 3–5. URL: <https://www.limesurvey.org/>.
- [237] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic. “A multimodal database for affect recognition and implicit tagging.” In: *IEEE Transactions on Affective Computing* 3.1 (Jan. 2012), pp. 42–55. ISSN: 19493045. DOI: 10.1109/T-AFFC.2011.25. URL: <http://ieeexplore.ieee.org/document/5975141/>.
- [238] R. H. Spector. *The Pupils*. Butterworths, 1990. ISBN: 040990077X. URL: <http://www.ncbi.nlm.nih.gov/pubmed/21250222>.
- [239] S. Sperandei. “Understanding logistic regression analysis.” In: *Biochimica Medica* 24.1 (2014), pp. 12–18. ISSN: 13300962. DOI: 10.11613/BM.2014.003. URL: <http://www.ncbi.nlm.nih.gov/pubmed/24627710><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3936971>.
- [240] B. Starfield. “Threads and yarns: Weaving the tapestry of comorbidity.” In: *Annals of Family Medicine* 4.2 (2006), pp. 101–103. ISSN: 15441709. DOI: 10.1370/afm.524. URL: <http://www.ncbi.nlm.nih.gov/pubmed/16569711><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1467013>.
- [241] G. Stemmler and J. Wacker. “Personality, emotion, and individual differences in physiological responses.” In: *Biological Psychology* 84.3 (July 2010), pp. 541–551. ISSN: 03010511. DOI: 10.1016/j.biopsycho.2009.09.012. URL: <http://www.ncbi.nlm.nih.gov/pubmed/19800934><https://linkinghub.elsevier.com/retrieve/pii/S0301051109001987>.

BIBLIOGRAPHY

- [242] B. Studer, B. Scheibehenne, and L. Clark. “Psychophysiological arousal and inter- and intraindividual differences in risk-sensitive decision making.” In: *Psychophysiology* 53.6 (June 2016), pp. 940–950. ISSN: 14698986. DOI: 10.1111/psyp.12627. URL: <http://doi.wiley.com/10.1111/psyp.12627>.
- [243] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler, and N. Sebe. “Ascertain: Emotion and personality recognition using commercial sensors.” In: *IEEE Transactions on Affective Computing* 9.2 (Apr. 2018), pp. 147–160. ISSN: 19493045. DOI: 10.1109/TAFFC.2016.2625250. URL: <https://ieeexplore.ieee.org/document/7736040/>.
- [244] J. A. Suhr and J. Tsanadis. “Affect and personality correlates of the Iowa Gambling Task.” In: *Personality and Individual Differences* 43.1 (July 2007), pp. 27–36. ISSN: 01918869. DOI: 10.1016/j.paid.2006.11.004. URL: <https://www.sciencedirect.com/science/article/pii/S0191886906004466>.
- [245] Y. Sun, M. S. Kamel, A. K. Wong, and Y. Wang. “Cost-sensitive boosting for classification of imbalanced data.” In: *Pattern Recognition* 40.12 (Dec. 2007), pp. 3358–3378. ISSN: 00313203. DOI: 10.1016/j.patcog.2007.04.009. URL: <https://www.sciencedirect.com/science/article/abs/pii/S0031320307001835>.
- [246] A. Suzuki, A. Hirota, N. Takasawa, and K. Shigemasu. “Application of the somatic marker hypothesis to individual differences in decision making.” In: *Biological Psychology* 65.1 (Dec. 2003), pp. 81–88. ISSN: 03010511. DOI: 10.1016/S0301-0511(03)00093-0. URL: <https://www.sciencedirect.com/science/article/pii/S0301051103000930>.
- [247] N. Systems. *Neurobehavioral Systems*. 2011. URL: <https://www.neurobs.com/> (visited on 04/05/2019).
- [248] K. Takahashi, S. Y. Namikawa, and M. Hashimoto. “Computational emotion recognition using multimodal physiological signals: Elicited using Japanese kanji words.” In: *2012 35th International Conference on Telecommunications and Signal Processing, TSP 2012 - Proceedings*. IEEE, July 2012, pp. 615–620. ISBN: 9781467311182. DOI: 10.1109/TSP.2012.6256370. URL: <http://ieeexplore.ieee.org/document/6256370/>.
- [249] P. K. Tan, T. J. Downey, E. L. Spitznagel, P. Xu, D. Fu, D. S. Dimitrov, R. A. Lempicki, B. M. Raaka, and M. C. Cam. “Evaluation of gene expression measurements from commercial microarray platforms.” In: *Nucleic Acids Research* 31.19 (Oct. 2003), pp. 5676–5684. ISSN: 03051048. DOI: 10.1093/nar/gkg763. URL: <http://www.ncbi.nlm.nih.gov/pubmed/14500831><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC206463><https://academic.oup.com/nar/article-lookup/doi/10.1093/nar/gkg763>.
- [250] L. I. Thompson. “Physiological Correlates of Affective Decision- Making in Anxiety and Depression.” Doctoral dissertation. City University of New York, 2017.

- [251] Tobii. *Tobii.com - Tobii is the world leader in eye tracking*. 2018. URL: <https://www.tobii.com/> (visited on 04/17/2019).
- [252] S. Tok, M. Koyuncu, S. Dural, and F. Catikkas. "Evaluation of International Affective Picture System (IAPS) ratings in an athlete population and its relations to personality." In: *Personality and Individual Differences* 49.5 (Oct. 2010), pp. 461–466. ISSN: 01918869. DOI: 10.1016/j.paid.2010.04.020. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0191886910002266>.
- [253] I. Tomb, M. Hauser, P. Deldin, A. Caramazza, H. Damasio, A. Bechara, and A. R. Damasio. "Do somatic markers mediate decisions on the gambling task?" In: *Nature Neuroscience* 5.11 (Nov. 2002), pp. 1103–1104. ISSN: 10976256. DOI: 10.1038/nn1102-1103. URL: <http://www.ncbi.nlm.nih.gov/pubmed/12403997>
<http://www.nature.com/articles/nn1102-1103>.
- [254] M. T. Tomlinson, D. Hinote, and D. B. Bracewell. "Predicting conscientiousness through semantic analysis of facebook posts." In: *AAAI Workshop - Technical Report*. Vol. WS-13-01. 2013, pp. 31–34. ISBN: 9781577356110. URL: <https://pdfs.semanticscholar.org/f2b7/320ec6a0f3173f6d49d5be60a8238e10736a.pdf>.
- [255] J. F. Trevor Hastie Robert Tibshirani. *The Elements of Statistical Learning*. Vol. 27. 2. 2009, 83–85. ISBN: 9780387848570. DOI: 10.1007/b94608. URL: <https://web.stanford.edu/~hastie/Papers/ESLII.pdf>
<http://www.springerlink.com/index/D7X7KX6772HQ2135.pdf>.
- [256] K. Uhlig, B. Leff, D. Kent, S. Dy, K. Brunnhuber, J. S. Burgers, S. Greenfield, G. Guyatt, K. High, R. Leipzig, C. Mulrow, K. Schmader, H. Schunemann, L. C. Walter, J. Woodcock, and C. M. Boyd. "A framework for crafting clinical practice guidelines that are relevant to the care and management of people with multimorbidity." In: *Journal of General Internal Medicine* 29.4 (Apr. 2014), pp. 670–679. ISSN: 15251497. DOI: 10.1007/s11606-013-2659-y. URL: <http://www.ncbi.nlm.nih.gov/pubmed/24442332>
<http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3965742>
<http://link.springer.com/10.1007/s11606-013-2659-y>.
- [257] S. Van Der Walt, S. C. Colbert, and G. Varoquaux. "The NumPy array: A structure for efficient numerical computation." In: *Computing in Science and Engineering* 13.2 (2011), pp. 22–30. ISSN: 15219615. DOI: 10.1109/MCSE.2011.37. URL: <http://ieeexplore.ieee.org/document/5725236/>.
- [258] G. K. Vincent and V. A. Velkoff. "The Older Population in the United States : 2010 to 2050, population estimates and projections." In: *Current population reports: Population estimates and projections*. May. 2010, pp. 1–16. URL: www.census.gov/population/www
<http://www.census.gov/content/dam/Census/library/publications/2010/demo/p25-1138.pdf>.

- [259] C. Vogeli, A. E. Shields, T. A. Lee, T. B. Gibson, W. D. Marder, K. B. Weiss, and D. Blumenthal. “Multiple chronic conditions: Prevalence, health consequences, and implications for quality, care management, and costs.” In: *Journal of General Internal Medicine*. Vol. 22. SUPPL. 3. Springer, Dec. 2007, pp. 391–395. DOI: 10.1007/s11606-007-0322-1. URL: <http://www.ncbi.nlm.nih.gov/pubmed/18026807><http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC2150598>.
- [260] T. G. Von Lueder and D. Atar. “Comorbidities and polypharmacy.” In: *Heart Failure Clinics* 10.2 (Apr. 2014), pp. 367–372. ISSN: 15517136. DOI: 10.1016/j.hfc.2013.12.001. URL: <http://www.ncbi.nlm.nih.gov/pubmed/24656112><https://linkinghub.elsevier.com/retrieve/pii/S155171361300158X>.
- [261] J. Wache. “The secret language of our body - Affect and personality recognition using physiological signals.” In: *ICMI 2014 - Proceedings of the 2014 International Conference on Multimodal Interaction*. 2014, pp. 389–393. ISBN: 9781450328852. DOI: 10.1145/2663204.2666290.
- [262] R. Wald, T. Khoshgoftaar, and C. Sumner. “Machine prediction of personality from Facebook profiles.” In: *Proceedings of the 2012 IEEE 13th International Conference on Information Reuse and Integration, IRI 2012*. IEEE, Aug. 2012, pp. 109–115. ISBN: 9781467322843. DOI: 10.1109/IRI.2012.6302998. URL: <http://ieeexplore.ieee.org/document/6302998/>.
- [263] B. G. Wallin. “Sympathetic nerve activity underlying electrodermal and cardiovascular reactions in man.” In: *Psychophysiology* 18.4 (1981), pp. 470–476.
- [264] E. U. Weber and E. J. Johnson. “Economic, and Neuroeconomic Explanations of Risk Preference Risk Preference: The Historical Context.” In: *Brain* (2009), pp. 127–144. DOI: 10.1016/B978-0-12-374176-9.00010-5.
- [265] L. L. Weed. “Medical records, patient care, and medical education.” In: *Irish Journal of Medical Science* 39.6 (June 1964), pp. 271–282. ISSN: 18634362. DOI: 10.1007/BF02945791. URL: <http://link.springer.com/10.1007/BF02945791>.
- [266] H. Wei, F. Zhang, N. J. Yuan, C. Cao, H. Fu, X. Xie, Y. Rui, and W. Y. Ma. “Beyond the words: Predicting user personality from heterogeneous information.” In: *WSDM 2017 - Proceedings of the 10th ACM International Conference on Web Search and Data Mining*. 2017, pp. 305–314. ISBN: 9781450346757. DOI: 10.1145/3018661.3018717.
- [267] I. B. Weiner, D. K. Freedheim, J. A. Schinka, and W. F. Velicer. *Handbook of psychology*. Wiley, 2003. ISBN: 0471384046. URL: https://books.google.pt/books/about/Handbook_of_Psychology_Personality_and_S.html?id=1BXf1s1ZBDwC&redir_esc=y.
- [268] *Welcome to Nolds' documentation! — Nolds 0.5.1 documentation*. URL: <https://choel.github.io/nolds/> (visited on 07/12/2019).

- [269] *Welcome to Python.org*. URL: <https://www.python.org/> (visited on 10/08/2017).
- [270] J. A. Weller, I. P. Levin, and A. Bechara. “Do individual differences in Iowa Gambling Task performance predict adaptive decision making for risky gains and losses?” In: *Journal of Clinical and Experimental Neuropsychology* 32.2 (Feb. 2010), pp. 141–150. ISSN: 13803395. DOI: 10.1080/13803390902881926. URL: <http://www.ncbi.nlm.nih.gov/pubmed/19484643><https://www.tandfonline.com/doi/full/10.1080/13803390902881926>.
- [271] N. S. Werner, S. Duschek, and R. Schandry. “Relationships between affective states and decision-making.” In: *International Journal of Psychophysiology* 74.3 (Dec. 2009), pp. 259–265. ISSN: 01678760. DOI: 10.1016/j.ijpsycho.2009.09.010. URL: <https://www.sciencedirect.com/science/article/abs/pii/S016787600900230X>.
- [272] WHO Regional Office for Europe. *The European health report 2005*. World Health Organization, WHO Regional Office for Europe, 2005, p. 178. ISBN: 92 890 1376 1. URL: <http://www.euro.who.int/en/health-topics/Life-stages/child-and-adolescent-health/publications/2005/european-health-report-2005-the.-public-health-action-for-healthier-children-and-populations>.
- [273] D. M. Witten and R. Tibshirani. “Covariance-regularized regression and classification for high dimensional problems.” In: *Journal of the Royal Statistical Society. Series B: Statistical Methodology* 71.3 (June 2009), pp. 615–636. ISSN: 13697412. DOI: 10.1111/j.1467-9868.2009.00699.x. URL: <http://doi.wiley.com/10.1111/j.1467-9868.2009.00699.x>.
- [274] I. H. Witten and E. Frank. *Data mining : practical machine learning tools and techniques*. Morgan Kaufman, 2005, p. 525. ISBN: 9780120884070.
- [275] I. H. Witten, E. Frank, and M. A. Hall. *Data mining : practical machine learning tools and techniques*. Morgan Kaufmann, 2011, p. 629. ISBN: 9780123748560.
- [276] T. Yamauchi and K. Xiao. “Reading Emotion From Mouse Cursor Motions: Affective Computing Approach.” In: *Cognitive Science* 42.3 (2018), pp. 771–819. ISSN: 15516709. DOI: 10.1111/cogs.12557.
- [277] S. Yilmaz and H. Kafadar. “Investigating the relationship between decision-making processes and cognitive processes, personality traits, and affect via the structural equation model in young adults.” In: *Applied Neuropsychology:Adult* (Mar. 2019), pp. 1–12. ISSN: 23279109. DOI: 10.1080/23279095.2019.1576690. URL: <https://www.tandfonline.com/doi/full/10.1080/23279095.2019.1576690>.

A P P E N D I X



THESIS OVERVIEW

This appendix includes a diagram with all the chapters of this thesis. In the main chapters are introduced the question that is answered and the respective outputs.

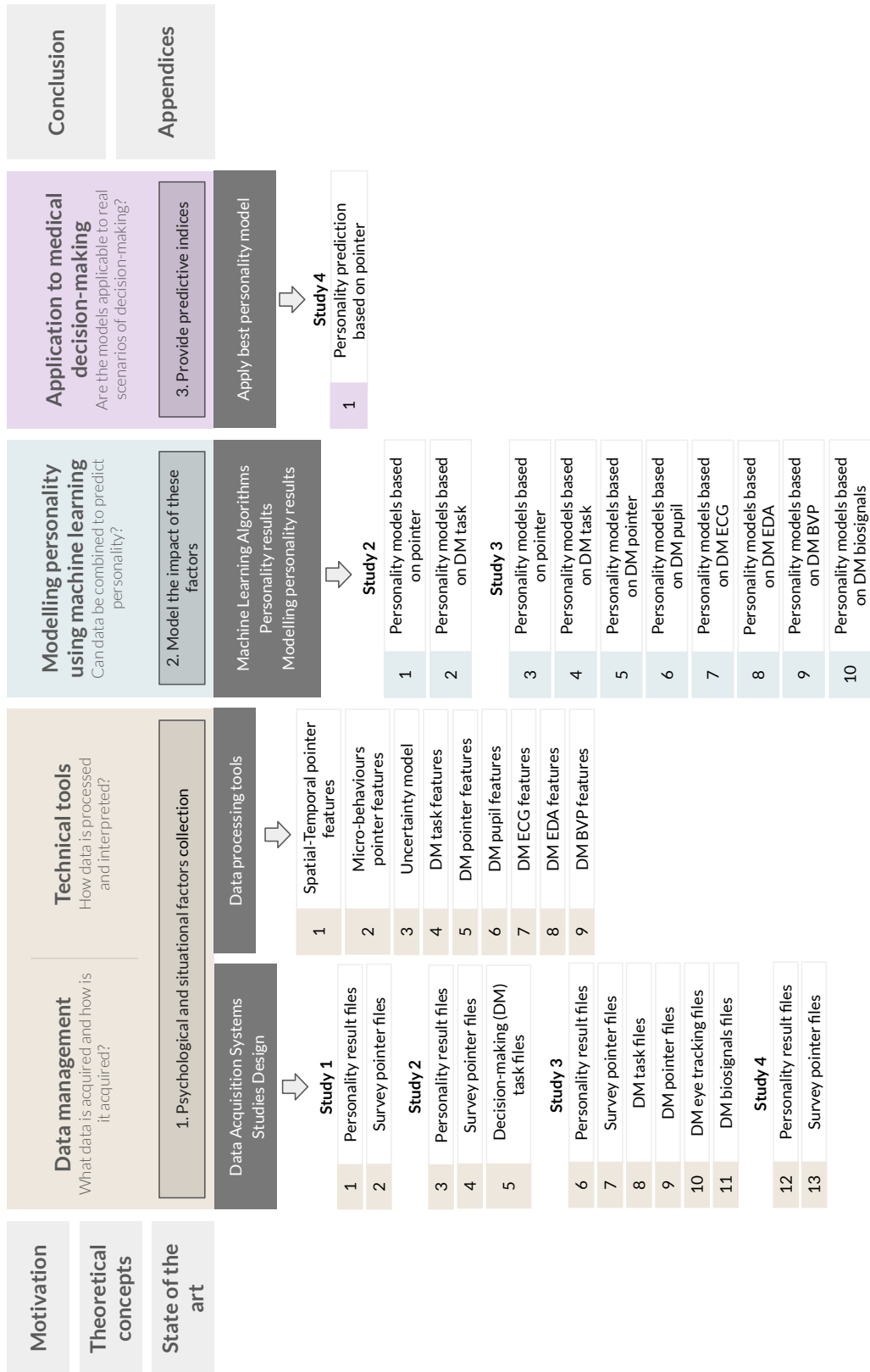


Figure A.1: Thesis structure with detailed outputs.

RESPONSE UNCERTAINTY MODEL

This appendix explains how the uncertainty predictive model was built. It is adapted from the published paper [72].

B.1 Introduction

In self-report questionnaires, for each item, a rating scale with a number of response alternatives is provided that allows the respondent to confirm the degree to which the statement is true or false. For several reasons, the respondent may feel more uncertain while rating particular items and this behaviour is clearly observed in the visual analysis of the mouse movement over time. While identifying features from the mouse movements (described in 5.1.3 and 5.1.4), we hypothesize whether behaviours, like how long a person hovers with the mouse over a question, how quickly a response is given, or whether a person revisits an items or corrects the previous response might be indicators of response uncertainty.

Although previous studies consistently used response times to assess response difficulty [55, 221, 282], some authors also explored, and confirmed, the influence of the mouse trajectory in predicting uncertainty, in terms of horizontal direction inversions [282] and deviation from the idealized straight-line trajectory [221]. More recently, Horwitz et al. [121], used mouse cursor trajectories to predict response difficulty, achieving a performance accuracy of between 74.28% and 79.11%. Significant predictors of uncertainty were horizontal directional inversions, hovering the mouse cursor over a question for more than 2s, and marking a response option for more than 2s [121].

Our aim was to create a machine-learning model that identifies events of response uncertainty using some of the previously described features of mouse movement while respondents processed and answered questionnaire items.

B.2 Methods

B.2.1 Features Extraction

Regarding that this part of the study has the aim of identifying a micro-behaviour feature from mouse interaction, we are still using the data from Study 2 to build the uncertainty predictive model, Most of the features used were stated in 5.1. However, in this case, the features were associated to each item of the questionnaire and not to a personality result (i.e. to each subject) and, therefore, the computation process of features extraction need to be adjusted in that respect. Both temporal, spatial and contextual features were used to detect items that evoked uncertainty:

- Length;
- Straightness;
- Temporal velocity;
- Accumulated time;
- Hovered answers;
- Selected answer ratio;
- Time before click;
- Pause before click;
- Distance from answer;
- <-turns;
- Correction within item;
- Revisit;
- Correction time;´
- Interactions.

To extract the features the constants were defined: $k_{pause} = 1 \text{ second}$; $k_{zapp} = 0.1 \text{ second}$; $k_{aband} = 10 \times \text{mean}(t_{item}) \text{ seconds}$. The last feature, **interactions**, is the only new feature, which corresponds to the number of interactions with each question (i.e., the number of times in each question).

B.2.1.1 Features Normalization

Distinct people express uncertainty differently. For example, maybe the time spent in a difficult question by a fast person is equal to the time spent in an easy question by a slower individual. Accordingly, the features were normalized for each person separately using the formula presented in equation B.1, where z_i represents the sample x_i after

normalization, \bar{x} and σ are the mean and standard deviation of the samples, respectively. This normalization is known as z-score [229]. Applying this transformation, the samples are reshaped so that its mean and standard deviation become 0 and 1, respectively [249].

$$z_i = \frac{x_i - \bar{x}}{\sigma} \quad (\text{B.1})$$

Nonetheless, with all the features normalized, it is only possible to identify the most difficult questions for each individual. In the hypothetical case of uncertainty in all questions (or a great part of them), this would be a problem. Therefore, the original values of each feature were also used to construct the model. Taking this into account, 30 features were used - 15 normalized and 15 not normalized.

Subsequently, all the features from all the participants were concatenated and each feature was individually normalized in order to standardize the range of the variables for all the participants.

B.2.2 Features Selection

There is a negative effect of using irrelevant features in machine learning systems. Some machine learning classifiers are not sensible enough to detect the influence of relevant features in the presence of many variables [239]. Taking this into account, it is advantageous to precede learning with a feature selection stage [274].

Accordingly, the highly correlated features were eliminated [274], since the information they provide is almost the same. The Pearson correlation coefficient was accessed and, if two features had an absolute coefficient higher than 0.9, one of them was left out.

B.2.3 Model Training and Testing

In order to train and test the uncertainty model, several examples of items showing response uncertainty and certainty were needed. These examples comprise a combination of features and a respective outcome (certainty or uncertainty). However, it was not known which items evoked, or not, uncertainty. To solve this problem, mouse movement videos of 6 individuals answering a 60 item questionnaire (360 questions in total) were observed and rated by three raters in terms of uncertainty or certainty. The final examples of items for training and testing were selected only if rated as uncertainty or certainty by at least 2 of the raters. In the end, 51 items were rated as uncertainty and 124 as certainty. Raters were asked to just rate an item in case there is any doubt and, therefore, the remaining 185 items were not rated by, at least, one rater.

The *10-fold cross validation* method was applied for model training and testing. In this procedure, the data is divided into ten approximately equal partitions, where one partition is used for testing and the other nine for training. This process is repeated ten times. In each iteration, the datasets change and, accordingly, every partition is used for both training and testing, and exactly once for testing. Finally, the ten estimated accuracies are averaged to obtain the overall accuracy.

B.2.4 Classification

The applied classification method was *Logistic Regression*, due to its effectiveness when the outcome variable is dichotomous (in this case, the outcome could be certainty or uncertainty). In this technique, the probability of occurrence of an event is estimated by fitting the data to a logistic curve. Accordingly, non-linear relationships between the input features and the outcome variable can be handled [184].

The fundamental mathematical concept underlying *Logistic Regression* is the logit. The logit is the natural logarithm of the odds ratio, which is the ratio between the probability of occurrence of an event (in this case, uncertainty) and the probability of non-occurrence of the same event. The logistic model has the form presented in equations B.2 and B.3, where p represents the probability of an event, β_i illustrates the regression coefficients and x_i are the input features [239].

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (\text{B.2})$$

Solving for p ,

$$p = \frac{1}{1 + e^{-(\beta_0 + \dots + \beta_n x_n)}} \quad (\text{B.3})$$

When $p \geq 0.5$ it is predicted $Y = 1$ (uncertainty), otherwise, $Y = 0$, where Y is the outcome variable [230]. From equation B.3, it is possible to verify that a positive β_i increases (and a negative β_i decreases) the probability of $Y = 1$.

B.2.5 Model Evaluation

In binary classification, data is constituted by two opposite classes, positives and negatives. Accordingly, the possible outcomes comprise True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). In this study, the positives are the questions linked to uncertainty.

The true positive rate, or *sensitivity*, and the true negative rate, or *specificity*, were computed [274]. In this case, the *sensitivity* represents the probability of a question that evokes uncertainty being classified as an instance of uncertainty, and it is described in equation B.4. *Specificity*, on the other hand, provides the probability of a question associated with certainty being correctly classified and it is illustrated by equation B.5.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (\text{B.4})$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (\text{B.5})$$

To estimate the performance of the model, accuracy was accessed. Accuracy is the ratio between the correct classifications and all the classifications [274], as it is shown in equation B.6.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (B.6)$$

Since the data is imbalanced (there are more certainty events than uncertainty occurrences), the most appropriate measure to evaluate the model performance is *f1 score*, defined in equation B.7 as the harmonic mean between *precision* and *recall*. *Recall* is a synonym of *sensitivity*, as it is possible to verify in equation B.8. *Precision*, on its turn, represents the probability of a certainty event being classified as an uncertainty event, as shown in equation B.9 [245].

$$f1\ score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (B.7)$$

Where

$$Recall = Sensitivity \quad (B.8)$$

And

$$Precision = \frac{FP}{FP + TN} \quad (B.9)$$

B.3 Results and Discussion

The highly correlated features were removed, as it was explained in section B.2.2. The features eliminated with this criterion were *time before click*, *hover selected answer*, *straightness normalized*, *revisits*, *revisits normalized* and *hovered answers normalized*. Therefore, the number of final features was 24.

Some features have more importance than others in the classification process. From equation B.3, it is possible to infer that features with higher regression coefficients are more relevant to the classification. Table B.1 shows the regression coefficients of the ten most relevant features ordered from the highest to the lowest absolute value.

Table B.1: Regression coefficients of the ten most relevant features.

Feature	Regression coefficient
<-Turn	1.47
Length normalized	1.23
Length	1.19
Distance from answer normalized	-0.93
Interactions	0.65
Accumulated time	0.61
Straightness	-0.49
Pause before click	0.31
Corrections between item	-0.31
Distance from answer	-0.29

The number of *<-turns* is the most relevant feature and, with a positive regression coefficient, it increases the probability of detecting an uncertainty event. Individuals thus tend to change the horizontal direction more frequently during a moment of uncertainty, probably due to hesitation between consecutive alternatives. This is in line with [282].

The *distance* travelled has a strong positive impact on the outcome, suggesting that respondents move the mouse from a possible answer to another while deciding which one to select. *Distance from answer* affected the result negatively, meaning that, although individuals travel longer distances during moments of uncertainty, they tend to maintain the mouse cursor closer to the selected alternative. Probably this is influenced by consecutive questions with opposite (or very different) responses. That is when a person moves directly from option 1 of an item to option 5 of the subsequent question, one of these items is associated with a large mean *distance from answer*. Nonetheless, in a question associated with uncertainty, where the travelled distance is long, this effect is attenuated.

Analysing the regression coefficient of *interactions*, it can be concluded that people visit items that arouse uncertainty more often. In these items, individuals take longer to answer (*accumulated time* has a positive and significant regression coefficient) and deviate more from the straight-line trajectory between successive answers (*straightness* is associated to a negative coefficient).

It is surprising that the number of corrections influences negatively the result. This means that when the number of corrections increases, the probability of identifying an uncertainty event decreases.

B.3.1 Model Evaluation

The model evaluation measures - *sensitivity*, *specificity* and *accuracy* - are presented in table B.2.

Table B.2: Model performance evaluation measures.

Sensitivity	Specificity	Accuracy	F1 Score
0.78	0.94	0.89	0.81

Regarding the model evaluation, the *sensitivity* obtained was 0.78, which means that the instances of uncertainty were correctly classified in 78% of the times. The *specificity* was 0.94 (i.e. the probability of a certainty event being correctly predicted is 94%). The classification of certainty versus uncertainty was correct in 89% of the cases. The estimated performance of the model was, therefore, better than that of [121]. This improvement might relate to the choice of features used to indicate uncertainty. Using *F1 score*, the estimated performance of the model was 0.81. Taking into account that uncertainty assessment concerns a subjective evaluation, the performance of the model is very good.

Following the application of the model to all participants' questions, the percentage of questions associated with uncertainty was computed. Figure B.1 shows the contrast of the mouse movements between the individuals with the minimum and maximum percentages of questions that evoked uncertainty, and the behaviours are clearly different, where the distance travelled is much higher in the latter.

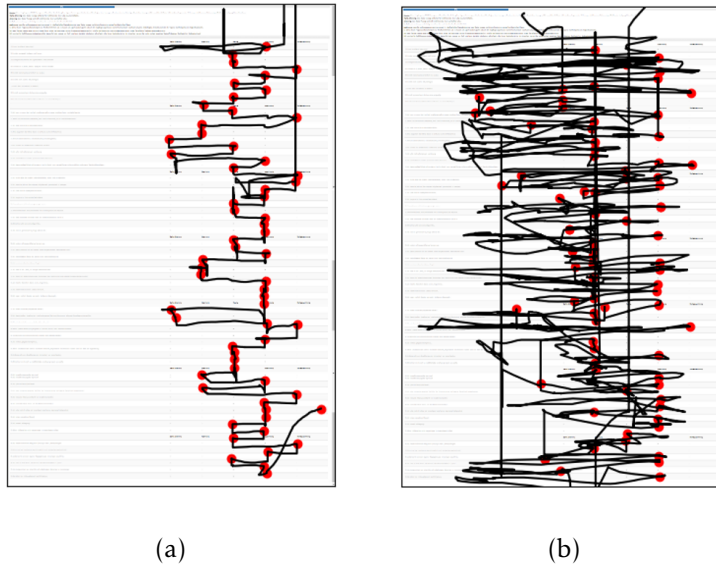


Figure B.1: Mouse movements of a questionnaire from the person with a) the minimum and b) the maximum percentage of uncertainty items.

A P P E N D I X



PERSONALITY QUESTIONNAIRE PROCEDURE

Liebe Studienteilnehmende



Ziel der Studie. Das Ziel dieser Online-Studie ist es, ein klares Bild davon zu bekommen, wie Sie sich in komplexen Situationen und in verschiedenen Kontexten verhalten. Anschliessend wird eine Auswahl an Personen, basierend auf der Online-Studie, für eine weitere Studie am Psychologischen Institut vorgenommen.

Ablauf der Studie. Bitte beachten Sie folgende Informationen:

- Insgesamt werden Sie drei aufeinanderfolgende Online-Fragebogen ausfüllen.
- Die Beantwortung der Fragebogen dauert insgesamt ca. 10 bis 20 Minuten.
- Wenn Sie wünschen, erhalten Sie für die Teilnahme an der Studie 0.5 VPN-Stunden.
- Beantworten Sie bitte die Fragebogen am PC, an einem ruhigen Ort, alleine und ohne Unterbrechung.
- Falls Sie die 0.5 VPN-Stunden wünschen und /oder gerne an der weiteren Studie teilnehmen, tippen Sie bitte Ihre Kontaktinformationen am Ende der Online-Studie ein.

Freiwilligkeit. An diesem Forschungsprojekt nehmen Sie freiwillig teil. Sie können zu jeder Zeit die Untersuchung abbrechen und Ihr Einverständnis ohne Angabe von Gründen widerrufen, ohne dass Ihnen dadurch persönliche Nachteile entstehen.

Datenschutz. Die erhobenen Daten werden anonym und unter Wahrung der Datenschutzbestimmungen ausschliesslich zu wissenschaftlichen Zwecken ausgewertet. Neben den Fragebogendaten werden nur die Personenkennzeichen Geschlecht und Geburtsdatum elektronisch gespeichert. Die Ergebnisse dieser Studie sollen in anonymisierter Form in wissenschaftlichen Veröffentlichungen verwendet werden. Sie können allerdings auch zu jedem Zeitpunkt verlangen, dass Ihre Daten vernichtet werden. Eine Begründung dafür ist nicht erforderlich.

Klicken Sie bitte oben rechts auf **"Weiter"**. Sie haben dann die Möglichkeit, uns mitzuteilen, dass Sie diese Informationen gelesen und verstanden haben und an dieser Studie teilnehmen möchten.

Falls Sie Fragen oder Anmerkungen haben, wenden Sie sich bitte an folgende E-Mail-Adresse: dina.rindlisbacher@uzh.ch

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

* Ich erkläre hiermit, alle Informationen gelesen und verstanden zu haben, und ich willige ein, an dieser Studie teilzunehmen.

Ja

Nein

i Zur Bearbeitung des Fragebogens klicken Sie bitte oben rechts auf "**Weiter**".

Falls Sie Fragen oder Anmerkungen haben, wenden Sie sich bitte an folgende E-Mail-Adresse: dina.rindlisbacher@uzh.ch

Vielen Dank für Ihre Unterstützung!

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

Hinweise: Dieser Fragebogen umfaßt 60 Aussagen, welche sich zur Beschreibung Ihrer eigenen Person eignen könnten. Lesen Sie bitte jede dieser Aussagen aufmerksam durch und überlegen Sie, ob diese Aussage auf Sie persönlich zutrifft oder nicht. Zur Bewertung jeder der 60 Aussagen steht Ihnen eine fünffach abgestufte Skala zur Verfügung. Klicken Sie bitte an:

Starke Ablehnung: wenn Sie der Aussage auf keinen Fall zustimmen oder sie für völlig unzutreffend halten.

Ablehnung: wenn Sie der Aussage eher nicht zustimmen oder sie für unzutreffend halten.

Neutral: wenn die Aussage weder richtig noch falsch, also weder zutreffend noch unzutreffend ist.

Zustimmung: wenn Sie der Aussage eher zustimmen oder sie für zutreffend halten. **Starke Zustimmung:** wenn Sie der Aussage nachdrücklich zustimmen oder sie für völlig zutreffend halten.

Es gibt bei diesem Fragebogen keine 'richtigen' oder 'falschen' Antworten, und Sie müssen kein Experte (keine Expertin) sein, um den Fragebogen angemessen beantworten zu können. Sie erfüllen den Zweck der Befragung am besten, wenn Sie die Fragen so wahrheitsgemäß wie möglich beantworten.

Bitte lesen Sie jede Aussage genau durch und klicken Sie als Antwort die Kategorie an, die Ihre Sichtweise am besten ausdrückt. Falls Sie Ihre Meinung nach dem Anklicken ändern sollten, klicken Sie einfach auf die Ihnen passende Antwort an.

Bitte bewerten Sie die 60 Aussagen zügig aber sorgfältig. Lassen Sie keine Aussage aus. Auch wenn Ihnen einmal die Entscheidung schwerfallen sollte, klicken Sie trotzdem immer eine Antwort an, und zwar die, welche noch am ehesten auf Sie zutrifft. Beginnen Sie bitte jetzt mit der Beantwortung!

	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
1. Ich bin nicht leicht beunruhigt.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2. Ich habe gerne viele Leute um mich herum.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
3. Ich mag meine Zeit nicht mit Tagträumereien verschwenden.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
4. Ich versuche zu jedem, dem ich begegne, freundlich zu sein.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
5. Ich halte meine Sachen ordentlich und sauber.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
6. Ich fühle mich anderen oft unterlegen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
7. Ich bin leicht zum Lachen zu bringen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
8. Ich finde philosophische Diskussionen langweilig.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
9. Ich bekomme häufiger Streit mit meiner Familie und meinen Kollegen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
10. Ich kann mir meine Zeit recht gut einteilen, so daß ich meine Angelegenheiten rechtzeitig beende.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
11. Wenn ich unter starkem Streß stehe, fühle ich mich manchmal, als ob ich zusammenbräche.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
12. Ich halte mich nicht für besonders fröhlich.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
13. Mich begeistern die Motive, die ich in der Kunst und in der Natur finde.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
14. Manche Leute halten mich für selbstsüchtig und selbstgefällig.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
15. Ich bin kein sehr systematisch vorgehender Mensch.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

16. Ich fühle mich selten einsam oder traurig.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
17. Ich unterhalte mich wirklich gerne mit anderen Menschen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
18. Ich glaube, daß es Schüler oft nur verwirrt und irreführt, wenn man sie Rednern zuhören läßt, die kontroverse Standpunkte vertreten.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
19. Ich würde lieber mit anderen zusammenarbeiten, als mit ihnen zu wetteifern.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
20. Ich versuche, alle mir übertragenen Aufgaben sehr gewissenhaft zu erledigen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
21. Ich fühle mich oft angespannt und nervös.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
22. Ich bin gerne im Zentrum des Geschehens.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
23. Poesie beeindruckt mich wenig oder gar nicht.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
24. Im Hinblick auf die Absichten anderer bin ich eher zynisch und skeptisch.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
25. Ich habe eine Reihe von klaren Zielen und arbeite systematisch auf sie zu.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
26. Manchmal fühle ich mich völlig wertlos.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
27. Ich ziehe es gewöhnlich vor, Dinge allein zu tun.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
28. Ich probiere oft neue und fremde Speisen aus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
29. Ich glaube, daß man von den meisten Leuten ausgenutzt wird, wenn man es zuläßt.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
30. Ich vertrödele eine Menge Zeit, bevor ich mit einer Arbeit beginne.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
31. Ich empfinde selten Furcht oder Angst.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
32. Ich habe oft das Gefühl, vor Energie überzuschäumen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
33. Ich nehme nur selten Notiz von den Stimmungen oder Gefühlen, die verschiedene Umgebungen hervorrufen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
34. Die meisten Menschen, die ich kenne, mögen mich.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
35. Ich arbeite hart, um meine Ziele zu erreichen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
36. Ich ärgere mich oft darüber, wie andere Leute mich behandeln.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree

	disagree				agree
37. Ich bin ein fröhlicher, gut gelaunter Mensch.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
38. Ich glaube, daß wir bei ethischen Entscheidungen auf die Ansichten unserer religiösen Autoritäten achten sollten.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
39. Manche Leute halten mich für kalt und berechnend.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
40. Wenn ich eine Verpflichtung eingehe, so kann man sich auf mich bestimmt verlassen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
41. Zu häufig bin ich entmutigt und will aufgeben, wenn etwas schiefgeht.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
42. Ich bin kein gut gelaunter Optimist.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
43. Wenn ich Literatur lese oder ein Kunstwerk betrachte, empfinde ich manchmal ein Frösteln oder eine Welle der Begeisterung.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
44. In Bezug auf meine Einstellungen bin ich nüchtern und unnachgiebig.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
45. Manchmal bin ich nicht so verlässlich oder zuverlässig, wie ich sein sollte.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
46. Ich bin selten traurig oder deprimiert.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
47. Ich führe ein hektisches Leben.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
48. Ich habe wenig Interesse, über die Natur des Universums oder die Lage der Menschheit zu spekulieren.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
49. Ich versuche stets rücksichtsvoll und sensibel zu handeln.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
50. Ich bin eine tüchtige Person, die ihre Arbeit immer erledigt.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
51. Ich fühle mich oft hilflos und wünsche mir eine Person, die meine Probleme löst.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
52. Ich bin ein sehr aktiver Mensch.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
53. Ich bin sehr wißbegierig.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
54. Wenn ich Menschen nicht mag, so zeige ich ihnen das auch offen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	1. Strongly disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly agree
55. Ich werde wohl niemals fähig sein, Ordnung in mein Leben zu bringen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
56. Manchmal war mir etwas so peinlich, daß ich mich am liebsten versteckt hätte	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

57. Lieber würde ich meine eigenen Wege gehen, als eine Gruppe anzuführen.

58. Ich habe oft Spaß daran, mit Theorien oder abstrakten Ideen zu spielen.

59. Um zu bekommen, was ich will, bin ich notfalls bereit, Menschen zu manipulieren

60. Bei allem, was ich tue, strebe ich nach Perfektion.

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

66%

Falls Sie die 0.5 VPN-Stunden wünschen und / oder Informationen zu der weiteren Studie erhalten möchten, tippen Sie bitte Ihre Kontaktinformationen ein:

Name:

Emailadresse:

Telefonnummer:

In dieses Feld dürfen nur Zahlen eingegeben werden.

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

A P P E N D I X



MISI II PROCEDURE

General Participant Information

Liebe Teilnehmerin,
Lieber Teilnehmer,

Therapeutisches Management bei Patienten mit komplexen „Disease-Disease Interactions“ (DDIs) kann eine Herausforderung darstellen. Eine verbesserte Methodik zur Erfassung von DDIs bildet eine wichtige Grundlage für neue Ansätze zur Ausbildung von Medizinern im Bereich DDI-Management.

Ziel der Studie

Das Ziel dieser Studie ist es, drei neu entwickelte Bewertungsskalen zur Einschätzung von DDIs zu validieren.

Informationen zum Versuchsablauf

Diese Studie umfasst 3 Termine mit einer Dauer von jeweils 45-60 Minuten. Bei jedem Termin bearbeiten Sie eine Fallvignette. Ihre Aufgabe bei den jeweiligen Fällen ist es, Ihre Urteile zu potentiellen DDIs anhand von vier verschiedenen Bewertungsskalen abzugeben. Die Bewertungen werden am PC abgegeben. Anschliessend stellen wir Ihnen Fragen zu den jeweiligen Fällen und Fragen zu Ihren Erfahrungen mit den drei Bewertungsskalen.

Freiwilligkeit

An diesem Forschungsprojekt nehmen Sie freiwillig teil. Sie können zu jeder Zeit die Untersuchung abbrechen und Ihr Einverständnis ohne Angabe von Gründen widerrufen, ohne dass Ihnen dadurch persönliche Nachteile entstehen.

Versicherung

Sie sind im Rahmen der Betriebs-Haftpflichtversicherung versichert. Die Versicherung übernimmt die Kosten der medizinischen Behandlung allfälliger gesundheitlicher Schäden, die im Rahmen dieser Studie auftreten können. Der verantwortliche Studienleiter wird in diesem Falle die notwendigen Schritte einleiten.

Vertraulichkeit/Datenschutz

Die erhobenen Daten werden anonym und unter Wahrung der Datenschutzbestimmungen ausschliesslich zu wissenschaftlichen Zwecken ausgewertet. Es werden neben den Daten nur die Personenkennzeichen elektronisch gespeichert. Die erhobenen Daten werden vor Ort gelagert in einer Datenbank für Forschungszwecke. Alle Personen, welche Sie im Rahmen dieser Studie betreuen, unterliegen der ärztlichen bzw. psychologischen Schweigepflicht und sind auf das Datengeheimnis verpflichtet. Nur dem *Versuchsleiter* ist die Zuordnung von erhobenen Daten und Personenkennzeichen bekannt. Sie können zu jedem Zeitpunkt verlangen, dass Ihre Daten vernichtet werden. Eine Begründung dafür ist nicht erforderlich. Sie haben die Möglichkeit, die gegebene Zustimmung zur Weiterverwertung der erhobenen Daten zu widerrufen.

Nutzen für die Versuchspersonen

Die Studie hat für Sie als Expertin bzw. Experte keinen direkten Nutzen.

Risiken und Unannehmlichkeiten

Keine.

Kosten

Die in dieser Information erwähnten Untersuchungen sind für Sie kostenlos.

Finanzierung

Die Studie wird durch die Klinik und Poliklinik für Innere Medizin finanziert.

Aufwandentschädigung

Es kann kein Entgelt entrichtet werden.

Kontaktpersonen

Bei Unklarheiten und unerwarteten oder unerwünschten Ereignissen, die während der Studie oder nach deren Abschluss auftreten, können Sie sich jederzeit an die unten stehenden Kontaktpersonen wenden:

.....

Ich erkläre hiermit, alle Informationen gelesen und verstanden zu haben.

Datum

Name/Vorname (Versuchsleiter):

Name/Vorname (Teilnehmer/ Teilnehmerin):

Informed Consent

Schriftliche Einwilligungserklärung zur Teilnahme an einem Studienprojekt. Bitte lesen Sie dieses Formular sorgfältig durch. Bitte fragen Sie, wenn Sie etwas nicht verstehen oder wissen möchten.

Titel der Studie	
Verantwortliche Institution	
Ort der Durchführung	
Leiter der Studie	
Teilnehmerin/Teilnehmer	Name und Vorname: Geburtsdatum: <input type="checkbox"/> weiblich <input type="checkbox"/> männlich

- Ich wurde von der unterzeichnenden Prüfperson mündlich und schriftlich über den Zweck und Ablauf des Projekts, über mögliche Vor- und Nachteile sowie über eventuelle Risiken informiert.
- Ich nehme an diesem Projekt freiwillig teil und akzeptiere den Inhalt der zum oben genannten Projekt abgegebenen schriftlichen Information. Ich hatte genügend Zeit, meine Entscheidung zu treffen.
- Meine Fragen im Zusammenhang mit der Teilnahme an diesem Projekt sind mir beantwortet worden.
- Ich bin einverstanden, dass der Leiter der Studie zu Prüf- und Kontrollzwecken in meine unverschlüsselten Daten Einsicht nehmen dürfen, jedoch unter strikter Einhaltung der Vertraulichkeit.
- Meine persönlichen Daten werden nur in verschlüsselter Form gespeichert.
- Ich kann jederzeit und ohne Angabe von Gründen von der Teilnahme zurücktreten, ohne dass ich deswegen Nachteile habe. Die bis dahin erhobenen Daten werden gelöscht.
- Die Haftpflichtversicherung des Spitals kommt für allfällige Schäden auf. Ich bin darüber informiert, dass eine Versicherung Schäden deckt, die auf das Forschungsprojekt zurückzuführen sind.

Ort, Datum	Unterschrift Teilnehmerin/Teilnehmer (in Druckbuchstaben)
------------	---

Bestätigung der Studienleitung: Hiermit bestätige ich, dass ich dieser Teilnehmerin/ diesem Teilnehmer Wesen und Bedeutung des Projekts erläutert habe. Ich versichere, alle im Zusammenhang mit diesem Projekt stehenden Verpflichtungen gemäss des geltenden Rechts zu erfüllen. Sollte ich zu irgendeinem Zeitpunkt während der Durchführung des Projekts von Aspekten erfahren, welche die Bereitschaft der Teilnehmerin/ des Teilnehmers zur Teilnahme an der Studie beeinflussen könnten, werde ich sie/ ihn umgehend darüber informieren.

Ort, Datum	Name und Vorname der informierenden Prüfperson (in Druckbuchstaben) Unterschrift der Prüfperson
------------	--

Handedness

Bitte geben Sie an, mit welcher Hand Sie...

- einen Brief schreiben: links rechts
- einen Ball auf ein Ziel werfen: links rechts
- einen Tennisschläger halten: links rechts
- ein Streichholz beim Anzünden halten: links rechts
- einen Hammer halten: links rechts
- eine Zahnbürste benutzen: links rechts
- eine Schere benutzen: links rechts
- einen Faden durch ein Nadelöhr führen: links rechts
- einen Besenstiel beim Fegen halten:
(Hand, die oben hält, angeben) links rechts
- Spielkarten austeilen: links rechts
- einen Schaufelstiel oben halten: links rechts
- den Deckel einer Dose aufschrauben: links rechts

Patientenfall 1

Instruktion

Der folgende Fragebogen enthält eine Liste aller möglichen Interaktionen zwischen den Diagnosen und den Medikamenten (sogenannte DDIs).

Es gibt drei Bewertungsskalen anhand derer die jeweiligen Interaktionspaare evaluiert werden können: Schweregrad, Wahrscheinlichkeit und Handlungspriorität.

Klicken Sie bitte mit der Maus auf den entsprechenden Kreis der drei Bewertungsskala an, um das Interaktionspaar zu bewerten.

Bewerten Sie bitte jede potenzielle DDI so genau und schnell wie möglich und immer in der gleichen Reihenfolge (Schweregrad, Wahrscheinlichkeit und Handlungspriorität).

Nutzen Sie bitte die vierte Bewertungsskala (Sicherheit), um anzugeben, wie sicher Sie sind über Ihre ersten drei Bewertungen.

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Eisenmangelanämie - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Metformin - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Lorazepam - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Metformin - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Lorazepam - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Gastritis Typ C	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Metformin - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Eisenmangelanämie - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisensulfat - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Esomeprazol - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Eisenmangelanämie - Neurodermitis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Neurodermitis - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Arterieller Hypertonus	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Neurodermitis - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Panikstörung	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Arterieller Hypertonus - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Neurodermitis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Lorazepam - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Neurodermitis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Lisinopril - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Neurodermitis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Diabetes mellitus Typ 2 - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gastritis Typ C - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisensulfat - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Neurodermitis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Diabetes mellitus Typ 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Lisinopril - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Arterieller Hypertonus	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisensulfat - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Neurodermitis - Eisensulfat	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Diabetes mellitus Typ 2 - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Eisensulfat - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Neurodermitis - Lorazepam	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Metformin	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Panikstörung	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Gastritis Typ C	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Diabetes mellitus Typ 2 - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

	Schweregrad				Wahrscheinlichkeit				Handlungspriorität				Sicher			
	1. Keine	2. Gering	3. Mittel	4. Hoch	1. Sehr unwahrscheinlich	2. Eher unwahrscheinlich	3. Eher wahrscheinlich	4. Sehr wahrscheinlich	1. Keine Priorität	2. Mittlere Priorität	3. Hohe Priorität	4. Notfall	1. Ganz unsicher	2. Etwas unsicher	3. Etwas sicher	4. Ganz sicher
Eisenmangelanämie - Gastritis type C	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Panikstörung - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisensulfat - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eisenmangelanämie - Arterieller Hypertonus	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Metformin - Feuchtigkeitscreme	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Gastritis Typ C	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Arterieller Hypertonus - Esomeprazol	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Neurodermitis - Lisinopril	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

This question is mandatory. Please complete all parts.

Schweregrad	Wahrscheinlichkeit	Handlungspriorität	Sicher
-------------	--------------------	--------------------	--------

Patientenfall 1

Instruktion

Geben Sie bitte Ihre Einschätzung der Gesamtkomplexität und des Schweregrades des Falles an, in dem Sie mit der Maus auf den entsprechenden Kreis der Bewertungsskala klicken. Klicken Sie diejenige Antwort an, die noch am ehesten für Sie zutrifft.

	Sehr niedrig	Eher niedrig	Weder noch	Eher hoch	Sehr hoch
Die Gesamtkomplexität des Falles ist	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Der gesamte Schweregrad des Falles ist	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Patientenfall 1

Instruktion

Der folgende Fragebogen enthält eine Reihe von Feststellungen, mit denen Sie Ihre Erfahrungen zu den drei Bewertungsskalen beschreiben können. Diese Feststellungen können genau für Sie zutreffen, eher zutreffen, eher nicht oder gar nicht zutreffen. Zur Beantwortung des Fragebogens klicken Sie bitte mit der Maus auf den entsprechenden Kreis. Bitte beantworten Sie jede Feststellung, auch wenn Sie einmal nicht sicher sind, welche Antwort auf Sie zutrifft. Klicken Sie dann diejenige Antwort an, die noch am ehesten auf Sie zutrifft.

	Stimmt nicht	Stimmt eher nicht	Stimmt eher	Stimmt
Es war mir klar, dass die jeweiligen Bewertungsskala die DDI aus anderen Perspektiven bewerten lassen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Unabhängig von meiner Kenntnis der DDIs, halte ich die Reihenfolge der Skalen (1. Schweregrad, 2. Wahrscheinlichkeit, 3. Handlungspriorität) für angemessen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

❏

