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Use of AI and Mathematical Modelling in Mental Health: Exploring Paroxysmal Supraventricular Tachycardia, Personality Disorders and Body Image Perception

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Abstract

This thesis applies AI and mathematical modelling to uncover psychological patterns in Paroxysmal Supraventricular Tachycardia (PSVT) and to study the evolution of mental health in relation to distorted Body Image Perception. To achieve these objectives, two separate studies were conducted, collecting data from 172 and 330 participants, respectively. In both cases, participants completed psychological questionnaires tailored to the specific aims of each study. Regarding the PSVT study, statistical and factor analyses were performed to identify key psychological patterns, while several machine learning models were tested to distinguish affected patients from controls. In addition, feature selection techniques helped investigate the key psychological scales. Focusing on the second study, a recursive mathematical model was developed to describe the evolution of a unidimensional psychological variable (PSYCH), which captures concerns about body shape, weight, self-esteem, and depressive tendencies. Implemented in MATLAB-Simulink, the model was analyzed through time-domain simulations, examining stability and long-term behavior. Through AI and mathematical modelling, this research identifies psychological patterns in PSVT and presents a new method for exploring body image dynamics within an engineering framework. The findings contribute to a deeper understanding of psychological and sociocultural factors, providing a foundation for further research and clinical applications.

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1. Introduction

In this thesis, artificial intelligence and mathematical modelling were applied to the context of mental health.

This work is divided into two applications that report on two different datasets. The first application is related to the psychological risk factors of Paroxysmal supraventricular tachycardia, while the second is about the link between body image and related psychological disorders.

For both applications, at least one model was trained and developed using real patient data collected for the two studies.

This chapter introduces the essential concepts of medicine and psychology related to PSVT and body image, which are necessary to understand the topic around which our work is conducted. Finally, the background literature on these topics is also reviewed.

1.1 Paroxysmal Supraventricular Tachycardia

Paroxysmal Supraventricular Tachycardia (PSVT) is a type of arrhythmia characterized by the sudden onset and termination of an abnormally fast heart rhythm originating above the ventricles[1]. The increased heart rate is caused by an abnormal electrical pathway in the heart that creates a reentrant circuit, repetitively transmitting the signal generated by the sinus node during each heartbeat[2]. Variants of PSVT include Atrioventricular Nodal Re-entrant Tachycardia, Atrial Flutter, Focal Atrial Tachycardia, and Wolff-Parkinson-White Syndrome [3].

Patients with PSVT frequently report experiencing palpitations, dizziness, shortness of breath, and chest discomfort, with the frequency and duration of episodes varying among individuals[1].

Diagnosis of PSVT is primarily based on electrocardiogram (ECG) findings and patient history. Management strategies include lifestyle modifications, vagal maneuvers, pharmacological interventions, and catheter ablation for recurrent or severe cases [1].

Modern research is increasingly highlighting a correlation between arrhythmia and psychological stress, and more broadly, mental health. Studies suggest that stress can influence cardiac electrophysiology, potentially triggering or exacerbating arrhythmic events. [4][5]

Given the role of psychological traits in PSVT episodes, incorporating mental health assessments and interventions may enhance treatment outcomes for affected individuals.

1.2 Body Image

Body Image is a concept that refers to the combination of thoughts, feelings, perceptions and beliefs that individuals have about their body.[6]

It consists of two distinct dimensions: a perceptual component, which refers to an individual's ability to accurately assess their own physical appearance, and an attitudinal component, which reflects the subjective emotions and evaluations a person holds about their body size and shape [7].

A positive body image exists when a person tends to accept, appreciate and respect their body. It is also associated with higher self-esteem, self-acceptance and healthy outlook and behaviors [8]. Additionally, a positive body image has been identified as a protective factor for eating disorders [9].

A distorted body image perception, on the other hand, can drive individuals to take extreme measures to modify their appearance. In the case of eating disorders such as anorexia nervosa, for example, this may manifest as self-starvation [10], while those experiencing muscle dysmorphia may engage in excessive gym training and steroid use to enhance muscle mass [11]. More in general, body image distortion is recognized as one of the most persistent symptoms of eating disorders, with its severity appearing to predict patients' long-term outcomes. [12] [13]

Given the crucial importance of body image in mental health and eating disorders, it is critical to develop assessment tools that measure its perception and allow prediction of the patient's relative mental state. This dissertation aims to develop a framework for studying the evolution of body image perception and its mental health implications.

1.3 Research Objectives

In this research work, 3 main macro-objectives are set.

In the first part, through data analysis with machine learning and statistical techniques, our aim is to identify psychological risk factors in the appearance of paroxysmal supraventricular tachycardia (PSVT). In doing so, classification models will be trained to predict the occurrence of the disease.

In the second part of the work, the objective is to develop a mathematical model that can describe the evolution of mental health related to body image and other factors such as societal influence and the actual body mass index.

Finally, while answering these psychology research questions, the goal is also to evaluate the validity of AI and mathematical modeling tools in the context of mental health.

1.4 Background Research

1.4.1 Mental Health and Cardiovascular Diseases

Research has increasingly highlighted the strong interconnection between mental health and cardiovascular diseases. Psychological factors such as stress, anxiety, and depression are known to influence the onset and progression of various cardiac conditions. Chronic stress and negative emotional states have been shown to contribute to potentially leading to arrhythmic episodes [5][4].

In their 2013 review, Peacock and Whang examined the influence of psychological distress on the occurrence of cardiac arrhythmias, particularly ventricular arrhythmias that can lead to sudden cardiac death. They concluded that psychological distress serves both as a predictor of high-risk cardiac conditions and as a direct trigger for arrhythmic events. The authors highlighted the challenges in studying this relationship due to the transient and unpredictable nature of emotions and arrhythmias. However, advancements in monitoring technologies and larger epidemiological datasets have facilitated more sophisticated research, underscoring the critical role of mental health in cardiovascular disease [4].

Rachel Lampert's 2016 article delved into how mental stress, particularly negative emotions like anger, can precipitate ventricular arrhythmias and sudden cardiac death. Through clinical studies involving patients with implantable cardioverter-defibrillators, Lampert demonstrated that anger could trigger ventricular arrhythmias. The proposed mechanisms include autonomic changes that alter cardiac repolarization, especially in patients with sympathetic denervation, potentially leading to lethal polymorphic ventricular tachycardias. The author suggested that interventions aimed at reducing negative emotions and their autonomic effects may be therapeutic for these patients [5].

Identifying and mitigating psychological risk factors could play a crucial role in managing PSVT more effectively and it is one of the objectives of this dissertation.

1.4.2 Mental Health and Body Image Perception

Cornelissen et al, in 2015, examined perceptual body image in women with a history of anorexia nervosa and healthy controls. Their findings indicated that women with a history of anorexia nervosa and a low BMI demonstrated high accuracy in body size estimation and heightened sensitivity to small BMI changes. However, as BMI increased within this group, their tendency to overestimate body size intensified in direct proportion to their BMI.[14] These findings are an example of the importance of the perceptional component of body image in an eating disorder.

Neurologically, support for such interactivity between perceptual and attitudinal aspects of body image comes from a more recent study by Preston et al. in 2016 [15] in which brain regions associated with affective body representation (such as the right anterior insular cortex and the anterior cingulate cortex) were demonstrated to be functionally connected to perceptual representation areas within the posterior parietal cortex, indicating that perceived body-size can directly influence attitudinal body image, even within healthy individuals.

An example on how changing the perception of body image can have a positive effect on body concerns and consequently on eating disorders and mental health is from the 2019 study by Irvine et Al.[16] The study tested a virtual reality (VR) training program to change the perception of the boundary between thin and fat bodies in women with high body image concerns. Two intervention groups received feedback to shift their categorizations toward higher BMIs, while a control group received no change. Results showed that both intervention groups changed their perceptions of body image and reduced concerns about shape, weight and nutrition, with more significant effects in the group with longer exposure times.[16]

These three studies suggest the importance of the relationship between an individual’s mental health and their body image. Finding a way to estimate a person's mental health in relation to his or her body image can therefore be vital both for diagnosing possible eating disorders and for having a way to intervene after they occur.

2. PSVT Project

In this part of the work, the relationship between PSVT and personality disorders was investigated. To obtain a psychological picture of the possible risks of the disease, statistical techniques and machine learning models were applied to the scoring of several psychological questionnaires.

This chapter first discusses the data collection process of the study, then reviews the psychological scales, and finally presents the methods and discusses the results obtained.

2.1 Data Collection Process

This study is part of a larger experimental project carried out by the research team led by Antonella Granieri, Professor at the Department of Psychology of the University of Turin. The research was designed as a case-control study, with participants divided into an experimental and a Control Group, each consisting of 86 subjects, for a total of 172 participants. [17]

Individuals included in the Experimental Group met specific selection criteria, ensuring the homogeneity and relevance of the sample. To be eligible, participants needed to have a confirmed diagnosis of PSVT while not presenting any history of autoimmune diseases. Additionally, they could not have suffered from cardiovascular conditions and individuals with hemoglobin levels below 11 were excluded, as well as those diagnosed with neurological disorders or thyroid dysfunctions. The study was also limited to individuals between the ages of 18 and 70, and those with metabolic disorders like diabetes mellitus were not included.[17]

The groups were matched based on key socio-demographic variables, as gender, age range, marital status, number of children, educational background, and academic qualifications. [17]

Before undergoing the psychological evaluations, participants signed a privacy consent document in accordance with Article 13 of Legislative Decree (30 June 2003). Additionally, they were given a socio-demographic questionnaire along with an information sheet outlining the study's objectives and references to the University of Turin’s Department of Psychological Research.[17]

The final dataset comprised 86 participants diagnosed with PSVT and an equal number of healthy individuals. Women represented 67% of the entire sample, and the gender distribution was kept equal within each group, ensuring that the number of healthy and PSVT-affected men and women remained the same.[17]

2.2 Psychological Scales considered for the PSVT Study

This section introduces the psychological questionnaires that patients filled out for this study and whose results were taken into account as problem variables in this research.

2.2.1 Toronto Alexithymia Scale (TAS-20)

The Toronto Alexithymia Scale (TAS-20) is a test that assesses emotional awareness and provides a measure of alexithymia [18]. It consists of 20 items, with scores ranging from a minimum of 20 to a maximum of 100 [19]. For instance, the test asks participants to rate their comfort level in silent interactions or how easily they can identify and describe their emotions [19]. Each question is answered on a 5-point scale, where 1 represents “strongly disagree” and 5 signifies “strongly agree” [19].

It is also possible to obtain three subscales from TAS-20[20]:

-Difficulty Identifying Feelings (DIF): difficulty in identifying feelings and in distinguishing between feelings and physical sensations.

-Difficulty Describing Feelings (DDF): difficulty in describing one's feelings to others.

-Externally Oriented Thinking (EOT): cognitive style oriented towards external reality.

[20]

These sub-scales were also considered in our work.

2.2.2 Multidimensional Health Locus of Control (MHLC)

The Multidimensional Health Locus of Control (MHLC) is a psychological test that measures a person's beliefs about the factors that influence their health. It consists of multiple subscales, each representing a different health's locus of control.[21]

-Internal (IN): extent to which individuals believe that their health depends on themselves and their actions.

-Chance (CH): extent to which individuals believe that their health depends on luck, fate or chance.

-Powerful Others (PO): extent to which individuals believe that their health depends on relevant people.

-Doctors (DO): extent to which individuals believe Doctors influence individual's health.

-Other People (OT): extent to which individuals believe other people influence their health.

[21]

Each question is answered on a 5-point scale, where 1 represents "strongly disagree" and 5 signifies "strongly agree"[21].

2.2.3 Coping Orientation to Problems Experienced (COPE)

The Coping Orientations to Problem Experienced (COPE) is a self-report questionnaire that considers several coping modes (Sica et al., 2008)[22]. The coping mechanisms considered are 15: Activity, Planning, Suppression of Competing Activities, Restraint, Seeking Information, Seeking Understanding, Emotional Venting, Positive Reinterpretation and Growth, Acceptance, Religious Engagement, Denial, Behavioral Disengagement, Mental Disengagement, and Substance Use [22].

The questionnaire consists of 60 items, asking respondents to rate how frequently they engage in a specific coping strategy (1 = 'I usually don't do it' to 4 = 'I almost always do it') [22] . The total score ranges from 60 to 240, with higher scores indicating better responses to stressful events.

The first Italian version includes 13 scales grouped into five broad dimensions:

- Social Support (SOSOC)(12 items; score range: 12 - 48)

-Avoidance Strategies (STRAEV) (16 items; score range: 16 - 64)

- Positive Attitude (ATTPOS) (12 items; score range: 12 - 48)

-Problem Orientation (ORPROB) (12 items; score range: 12 - 48)

-Religion (8 items; score range: 8 - 32) [16]. The Religion category was later replaced by Transcendent Orientation (ORTRAS).

[22]

2.2.4 Minnesota Multiphasic Personality Inventory-2 (MMPI-2)

The original version of the Minnesota Multiphasic Personality Inventory-2 (MMPI-2) was developed in 1989 by Butcher, Dahlstrom, Graham, and Tellegen. This self-report questionnaire assesses major personality traits and emotional disorders and consists of 567 true-false items. It includes six validity scales, ten clinical scales, 15 content scales, and 15 supplementary scales. The Italian version of the test was curated by Sirigatti, Pancheri, Narbone and

Biondi in 1994. The validity of the translation was verified using the bilingual test-retest technique.[23]

The following are the tables describing the MPII-2's psychological scales used in our data. These Tables are taken from a previous dissertation about this topic: A.Rebelo, 2022 [24].

MPII-2: CLINICAL SCALES		
ACRONYM	NAME	DESCRIPTION
Hs	Hypochondriasis	Detects body language.
Hy	Hysteria	Detects if the subject is aware of their vulnerabilities.
Pd	Psychotic Deviate	Detects if the subject respects the rules of the society and measures signs of conflict, anger, struggle.
mf	Masculinity/ Femininity	Detects gender-oriented behaviours or interests.
Pa	Paranoia	Measures intensity of sensitivity, suspiciousness, trust.
Pt	Psychasthenia	Measures intensity of worry, obsessiveness, doubts.
Sc	Schizophrenia	Detects unique thoughts and social withdrawal.
Ma	Mania	Measures level of excitement.

Si	Social Introversion	Measures orientation with people.

Table 1: Clinical Scales for MMPI-2

[24]

MPII-2: SUPPLEMENTAL SCALES		
ACRONYM	NAME	DESCRIPTION
Es	Ego-Strength scale	Measures personal coping skills, sense of reality, bodily functionality and psychological stability.
R	Repression Scale	Measures the degree of emotionality and impulsivity.
OH	Over-Controlled Hostility Scale	Determines convicts who have strong impulses with unconscious restraint against aggressive expression.
DO	Dominance Scale	Measures effective social dominance.
MDs	Marital Distress Scale	Determines issues in marriage.
Aps	Addictions Potential Scale	Measures the potential to become addicted to substance abuse.
Aas	Addictions Acknowledgement scale	Works together with Aps to measure the severity of addictions.

Table 2: MMPI-2 Supplemental Scales

[24]

MPII-2: CONTENT SCALES		
ACRONYM	NAME	DESCRIPTION
Frs	Fears	Measures specific and general fears.
Anx	Anxiety	Measures symptoms of anxiety, nervousness, physical issues or worry in general.
Obs	Obsessiveness	Measures decision-making challenges, excessive ruminating, and resistance to change.
Dep	Depression	Detects low mood, low energy, suicide thoughts, and other depression symptoms.
Hea	Health Concerns	Measures health concerns and physical issues.
Biz	Bizarre Mentation	Measures the presence of schizophrenic thought processes.
Ang	Anger	Measures emotions and actions of anger.
Asp	Antisocial Practices	Measures expression of attitudes that are not conforming and potential problems with authority.
cyn	Cynicism	Measures suspicion and mistrust of others and their intentions.
tpa	Type A Behaviour	Measures impatience, irritability, and competitiveness.

L_ se	Low Self Esteem	Measures negative beliefs about oneself, one's abilities and one's capacity to submit
sod	Social Discomfort	Measures preference to solitude and getting anxious when meeting new individuals.
fam	Family Problems	Measures anger, resentment, and little or no support from family.
wrk	Work Interference	Measures behavioural patterns that result in mediocre performance at work.
trt	Negative Treatment Indicators	Measures pessimism and hesitation to reveal personal information to others.

Table 3: MMPI-2 - Content Scales

[24]

MPII-2: VALIDITY SCALES		
ACRONYM	NAME	DESCRIPTION
L	Lie	This scale detects lies when the subject tries to pretend that they are better than they actually are.
F	Infrequency	This scale detects lies when the subject tries to pretend that they are worse than they actually are.
K	K-Correction	This scale backs up L and F scales by showing levels of defensiveness.

Fb	F back	This is the same as the F scale but detected in the last half of the test.

Table 4: MMPI-2 Validity Scales

[24]

2.2.5 Inventory of Stressful and Traumatic Life Events

This test assesses the presence of traumatic or stressful experiences in individuals. It consists of 29 items, with 27 being closed-ended questions and 2 open-ended ones [17]. Each item begins with a dichotomous Yes/No question. If the response is negative, the test moves on to the next item. However, if the response is positive, additional follow-up questions require answers on a scale from 1 to 5 for a more detailed evaluation [17].

Further questions explore specific aspects of the event, such as the subject's age at the time of occurrence, the level of distress experienced, the frequency with which the event is recalled, and how often it has recurred throughout their life [17]. If the experience happened multiple times, the subject is also asked whether they consider it the most distressing event they have encountered [17].

2.3 Methods and Results for PSVT study

2.3.1 Paired t-test

As a first step of this work, a paired t-test was conducted over all the data and features considered for the study.

The paired sample *t*-test is a statistical procedure that aims to determine the mean difference between two observations and to establish if it is zero. In the first case, it is said that the Null Hypothesis is confirmed, otherwise there is the realization of the Alternative Hypothesis. Main assumptions of this procedure are that dependent variables must be continuous, normally distributed, approximately normally distributed and without outliers. Additionally, the observation should be independent of each other. [25]

Two scores are obtained from this procedure: p-value, that represents the probability of observing the test results under the null hypothesis, and t statistic, the test statistic for the couples of observations. The lower is the p-value for a particular feature, the lower is the support for the null hypothesis for that feature. A cut-off can be chosen to determine the statistical significance to consider. [25]

The two groups considered for the analysis were those formed by the samples suffering from PSVT and the control group. The objective was to observe the distance between the two groups and to identify the scales for which this distance was greatest. The chosen threshold for p-value amounts to 0.05.

The following table shows the results obtained.

Questionnaire	Feature	p-values	t-statistic
TAS-20	TAS-20	0,191951	1,315287
	DIF	0,115479	1,590302
	DDF	0,375155	0,891543
	EOT	0,849946	0,189765
MHLC	IN	0,004621	-2,90937
	CH	0,041611	2,068722
	PO	0,002587	3,104719
	DO	0,058555	1,917332
	OT	0,001817	3,219955
COPE	SOSOC	0,154226	1,437575
	STRAEV	0,919253	0,101676
	ATTPOS	0,400531	0,844914
	ORPROB	0,2411	-1,18049
	ORTRAS	0,005477	2,850463
MMPI-2	L	0,271445	1,106934
	K	0,166364	1,395954
	F	0,82655	-0,2198
	Hs	0,000861	3,454832
	D	0,019305	2,384947
	Hy	0,024963	2,282396

	Pd	0,168216	1,38981
	Mf	0,379709	-0,88303
	Pa	0,445792	0,76601
	Pt	0,300191	1,04238
	Sc	0,356711	0,926691
	Ma	0,710012	0,373088
	Si	0,197221	1,299689
	D1	0,043866	2,045811
	D2	0,930763	0,087142
	D3	0,00954	2,652193
	D4	0,267861	1,11531
	D5	0,05415	1,952671
	Hy1	0,346184	-0,94728
	Hy2	0,635986	-0,47503
	Hy3	0,037009	2,118993
	Hy4	0,001039	3,396745
	Hy5	0,970978	-0,03649
	Pd1	0,027002	2,250458
	Pd2	0,049333	-1,99422
	Pd3	0,629703	-0,4839
	Pd4	0,578095	0,558318
	Pd5	0,713405	0,368516
	Pa1	0,514529	0,654544
	Pa2	0,190321	1,320174

	Pa3	0,643719	0,464161
	Sc1	0,676247	0,419035
	Sc2	0,346332	0,946983
	Sc3	0,478665	0,711593
	Sc4	0,319244	1,001882
	Sc5	0,249695	1,159017
	Sc6	0,044651	2,038075
	Ma1	0,045735	-2,02759
	Ma2	0,072796	1,816649
	Ma3	0,384628	-0,87391
	Ma4	0,027441	2,243852
	Si1	0,726512	0,350927
	Si2	0,235738	1,194158
	Si3	0,479576	0,710116
	Anx	0,00573	2,834684
	Frs	0,008605	2,689785
	Obs	0,074208	1,807586
	Dep	0,291926	1,06049
	Hea	0,001341	3,316871
	Biz	0,688273	0,402573
	Ang	0,201172	1,288199
	Cyn	0,600031	-0,52633
	Asp	0,215143	-1,24886
	Tpa	0,491998	0,690121

	L.se	0,437415	0,780243
	Sod	0,747903	0,32245
	Fam	0,18457	1,337676
	Wrk	0,034104	2,153594
	Trt	0,186108	1,332957
	A	0,204779	1,277857
	R	0,941922	-0,07307
	Es	0,069424	-1,83889
	Ma-R	0,453406	0,753208
	Fb	0,018852	2,394282
	O-H	0,42587	-0,80012
	Do	0,100153	-1,66222
	Re	0,067819	-1,84979
	Mt	0,138371	1,495948
	Gm	0,00553	-2,84712
	Gf	0,426662	0,798749
	Ps-Pk	0,098324	1,671384
	Mds	0,461216	0,740203
	Aps	0,610331	0,511495
	Aas	0,746468	0,324352
N Trauma	N Traumi	0,009724	2,645177

Table 5: Paired t-test

According to the chosen criterion (p-value less than 0.05), this is the list of features found significant:

	pvalues	tstat
Hs	0,000861	3,454832
Hy4	0,001039	3,396745
Hea	0,001341	3,316871
OT	0,001817	3,219955
PO	0,002587	3,104719
IN	0,004621	-2,90937
ORTRAS	0,005477	2,850463
Gm	0,00553	-2,84712
Anx	0,00573	2,834684
Frs	0,008605	2,689785
D3	0,00954	2,652193
N Traumi	0,009724	2,645177
Fb	0,018852	2,394282
D	0,019305	2,384947
Hy	0,024963	2,282396
Pd1	0,027002	2,250458
Ma4	0,027441	2,243852
Wrk	0,034104	2,153594
Hy3	0,037009	2,118993
CH	0,041611	2,068722
D1	0,043866	2,045811

Sc6	0,044651	2,038075
Ma1	0,045735	-2,02759
Pd2	0,049333	-1,99422

Table 6: Paired t-test , Best Features

2.3.2 Cohen's D

Cohen's d is a statistical measure used to quantify the effect size between two groups, indicating the standardized difference in means. It is particularly useful in the context of hypothesis testing, helping researchers understand the magnitude of an effect beyond mere statistical significance. A Cohen's d value of 0.2 is considered a small effect, 0.5 a medium effect, and 0.8 or higher a large effect [26].

The formula for Cohen's d is:

$$d = \frac{\overline{X_1} - \overline{X_2}}{s_p}$$

Where at the numerator there is the difference between the means of the two groups, while at the denominator the pooled standard deviation, calculated as

$$s_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$$

[26]

In the thesis we applied this statistical measure to our data to identify the most significant features. Again, the two groups considered were the PSVT and Control groups. As a Criterion adopted, we considered significant the features with a Cohen's d value greater than 0.2 in modulus.

The following are the results encountered:

Scale	**Sub-Scale**	**Cohen's d**
Tas 20	TAS-20	0,208218
	DIF	0,245479
	DDF	0,141388
	EOT	0,028195
MHLC	IN	-0,46191
	CH	0,306926
	PO	0,460917
	DO	0,294841
	OT	0,491491
COPE	SOSOC	0,217969
	STRAEV	0,015939
	ATTPOS	0,120222
	ORPROB	-0,18105
	ORTRAS	0,401627
MMPI	L	0,150259
	K	0,191732
	F	-0,03355

	Hs	0,502027
	D	0,37686
	Hy	0,389862
	Pd	0,206383
	Mf	-0,12702
	Pa	0,112832
	Pt	0,147846
	Sc	0,117064
	Ma	0,053343
	Si	0,198924
	D1	0,299128
	D2	0,012755
	D3	0,419161
	D4	0,155783
	D5	0,294872
	Hy1	-0,1429
	Hy2	-0,07609
	Hy3	0,324843
	Hy4	0,527332
	Hy5	-0,00551
	Pd1	0,309214
	Pd2	-0,25994
	Pd3	-0,06919
	Pd4	0,086302

	Pd5	0,057673
	Pa1	0,095896
	Pa2	0,204293
	Pa3	0,070163
	Sc1	0,062019
	Sc2	0,138474
	Sc3	0,097061
	Sc4	0,144142
	Sc5	0,180772
	Sc6	0,283066
	Ma1	-0,34477
	Ma2	0,267288
	Ma3	-0,12719
	Ma4	0,330503
	Si1	0,053152
	Si2	0,186863
	Si3	0,109706
	Anx	0,454384
	Frs	0,427821
	Obs	0,252531
	Dep	0,158227
	Hea	0,475965
	Biz	0,057463
	Ang	0,192632

	Cyn	-0,08681
	Asp	-0,19219
	Tpa	0,103636
	L.se	0,117609
	Sod	0,052275
	Fam	0,192066
	Wrk	0,304164
	Trt	0,198724
	A	0,194928
	R	-0,01155
	Es	-0,26782
	Ma-R	0,115876
	Fb	0,307501
	O-H	-0,1064
	Do	-0,23657
	Re	-0,24958
	Mt	0,21535
	Gm	-0,45463
	Gf	0,119335
	Ps-Pk	0,25099
	Mds	0,106457
	Aps	0,071378
	Aas	0,045977

N Trauma	N Traumi	0,378934

Table 7: Cohen's D results

The features found significant according to the criterion "|Cohen'D| > 0.02" are:

Sub-Scale	**Cohen's d**	**|Cohen's d|**
Hy4	0,527331514	0,527331514
Hs	0,502027019	0,502027019
OT	0,491490834	0,491490834
Hea	0,475964559	0,475964559
IN	-0,461911747	0,461911747
PO	0,460917417	0,460917417
Gm	-0,454631818	0,454631818
Anx	0,454383961	0,454383961
Frs	0,427820556	0,427820556
D3	0,419160943	0,419160943
ORTRAS	0,401627047	0,401627047
Hy	0,389862364	0,389862364
N Traumi	0,378933795	0,378933795
D	0,376859838	0,376859838
Ma1	-0,344769482	0,344769482
Ma4	0,330503206	0,330503206
Hy3	0,324843201	0,324843201

Pd1	0,309214018	0,309214018
Fb	0,307501343	0,307501343
CH	0,306926479	0,306926479
Wrk	0,304163744	0,304163744
D1	0,299128171	0,299128171
D5	0,294871739	0,294871739
DO	0,29484121	0,29484121
Sc6	0,283065705	0,283065705
Es	-0,267816432	0,267816432
Ma2	0,267287602	0,267287602
Pd2	-0,259941701	0,259941701
Obs	0,252530684	0,252530684
Ps-Pk	0,250990005	0,250990005
Re	-0,249576459	0,249576459
DIF	0,245479495	0,245479495
Do	-0,236569234	0,236569234
SOSOC	0,217969406	0,217969406
Mt	0,215349712	0,215349712
TAS-20	0,208217517	0,208217517
Pd	0,206382644	0,206382644
Pa2	0,204292556	0,204292556

Table 8: Cohen's D, best features

2.3.3 Comparing the two groups in terms of psychological thresholds

For some of the scoring of the subscales considered in the project, there are thresholds that identify the level of severity of the psychological disorder in question [27] [18]. In this section we computed the mean for the two groups and compared with the thresholds (when present), to see which scales from one group to another (PSVT and Controls) belong to different levels. For the scales without a threshold, only the means were computed and compared.

Scale	Feature	PSVT	Control
TAS-20	TAS-20	non-alexithymia (49.186)	non-alexithymia (46.581)
	DIF	47.328	42.72
	DDF	54.744	52
	EOT	47.151	46.802
MHLC	IN	19.442	22.302
	CH	17.012	15.256
	PO	23.128	20.814
	DO	10.988	10.035
	OT	12.093	10.767
COPE	SOSOC	34.035	32.384
	STRAEV	27.047	26.942
	ATTPOS	35.14	34.337

	ORPROB	34.512	35.698
	ORTRAS	23.849	21.756
MMPI-2	L	Modal (53.244)	Modal (52.012)
	K	Modal (53.919)	Modal (51.895)
	F	Modal (46.186)	Modal (46.477)
	Hs	Moderate (63.349)	Moderate (56.674)
	D	Moderate (55.047)	Modal (50.802)
	Hy	Modal (54.116)	Modal (49.965)
	Pd	Modal (52.779)	Modal (50.907)
	Mf	Modal (49.07)	Modal (50.291)
	Pa	Modal (51.14)	Modal (49.988)
	Pt	Modal (52.767)	Modal (51.279)
	Sc	Modal (52.756)	Modal (51.674)
	Ma	Modal (49.895)	Modal (49.302)
	Si	Modal (53.663)	Modal (51.756)
	D1	Low (59.209)	Low (55.709)
	D2	Low (52.198)	Low (52.058)
	D3	Moderate (63.907)	Low (58.314)
	D4	Low (57.605)	Low (55.651)
	D5	Low (57.081)	Low (53.709)
	Hy1	Low (47.465)	Low (48.779)
	Hy2	Low (42.605)	Low (43.244)
	Hy3	Moderate (61.547)	Low (57.209)
	Hy4	High (66.07)	Low (58.942)

	Hy5	Low (49.988)	Low (50.047)
	Pd1	Low (54.14)	Low (50.849)
	Pd2	Low (48.977)	Low (51.36)
	Pd3	Low (50.163)	Low (50.756)
	Pd4	Low (53.151)	Low (52.233)
	Pd5	Low (51.86)	Low (51.116)
	Pa1	Low (55.663)	Low (54.453)
	Pa2	Low (52.035)	Low (49.616)
	Pa3	Low (42.128)	Low (41.547)
	Sc1	Low (54.663)	Low (53.907)
	Sc2	Low (57.942)	Low (56.186)
	Sc3	Low (55.884)	Low (54.558)
	Sc4	Low (56.977)	Low (55.186)
	Sc5	Low (54.337)	Low (52.105)
	Sc6	Moderate (60.256)	Low (56.349)
	Ma1	Low (48.535)	Low (51.756)
	Ma2	Low (47.465)	Low (44.791)
	Ma3	Low (48.5)	Low (49.698)
	Ma4	Low (54.035)	Low (50.267)
	Si1	Low (51.547)	Low (51.058)
	Si2	Low (50.547)	Low (48.558)
	Si3	Low (54.942)	Low (53.965)
	Anx	Low (57.733)	Low (53.547)
	Frs	Low (58.128)	Low (53.547)

	Obs	Low (53.709)	Low (51.372)
	Dep	Low (53.047)	Low (51.465)
	Hea	Moderate (60.93)	Low (55.279)
	Biz	Low (53.395)	Low (52.837)
	Ang	Low (51.5)	Low (49.593)
	Cyn	Low (54.593)	Low (55.43)
	Asp	Low (50.081)	Low (51.779)
	Tpa	Low (51.047)	Low (50.116)
	L.se	Low (52.442)	Low (51.372)
	Sod	Low (52.674)	Low (52.163)
	Fam	Low (51.302)	Low (49.57)
	Wrk	Low (54.291)	Low (51.535)
	Trt	Low (54.349)	Low (52.465)
	A	Low (56.686)	Low (54.698)
	R	Low (53.093)	Low (53.198)
	Es	Low (43.047)	Low (46.081)
	Ma-R	High (53.442)	High (52.279)
	Fb	Valid (54.779)	Valid (51.477)
	O-H	Low (47.919)	Low (48.953)
	Do	Low (43.767)	Low (45.93)
	Re	Low (48.337)	Low (50.756)
	Mt	Low (55.826)	Low (53.651)
	Gm	Low (42.872)	Low (47.477)
	Gf	Low (47.302)	Low (46.244)

	Ps-Pk	Low (53.628)	Low (51.256)
	Mds	Low (50.779)	Low (49.744)
	Aps	Low (45.977)	Low (45.337)
	Aas	Low (52.988)	Low (52.453)
N Trauma	N Trauma	4.314	3.36

Table 9: Comparison of PSVT and Control group in terms of Psychological thresholds

According to this criterion, these are the features found significant:

Feature	PSVT	Control
Hy4	High (66.07)	Low (58.942)
Hea	Moderate (60.93)	Low (55.279)
D3	Moderate (63.907)	Low (58.314)
Hy3	Moderate (61.547)	Low (57.209)
D	Moderate (55.047)	Modal (50.802)
Sc6	Moderate (60.256)	Low (56.349)

Table 10: Psychological thresholds, best features

2.3.4 Greedy search with Sequential Feature Selector

Continuing with the goal of finding the most important psychological scales in this section we focus on the Sequential Feature Selector.

Sequential Feature selection is a greedy search technique used to reduce the initial dimension of the feature space into a smaller one. The objective is to find the most relevant features for the problem[28]. In this work, the implementation of this technique that was chosen is the one from the MLxtend python library.

The Sequential Feature Selector (SFS) from MLxtend is a powerful tool for feature selection in machine learning. It operates by iteratively adding or removing features based on their contribution to the predictive performance of a machine learning model. SFS can be implemented in both forward and backward selection modes, allowing users to either start with no features and build up to a specified number or begin with all features and eliminate those that do not enhance model accuracy. This method not only helps in improving model performance by reducing overfitting but also enhances interpretability by selecting the most relevant features. By using cross-validation, SFS ensures that the selected features are robust and generalizable to unseen data. [28]

The strength of this tool, which differentiates it from other implementations, is that it has embedded a floating variant that adds a conditional inclusion or exclusion step to remove features once they are excluded or included. The goal of this additional step is to consider a larger number of combinations of features. [28]

Another advantage of this tool, with respect to Recursive Feature Elimination from sci-kit-learn for example, is that it permits to select the features based on a metric selected from the user, instead of considering feature weight coefficients or feature importance.[28]

In this work, we performed Sequential Feature Selector to our data using Leave-One-Out cross validation and accuracy as a metric.

The models that were considered were Logistic Regression, Linear Discriminant Analysis, Random Forest, Support Vector Machines (with polynomial and radial Kernel) and Quadratic Discriminant Analysis. The implementation and API calls of the scikit-learn library in python was used for all models. [29]

Both the floating and standard variants were proved. No hyperparameter selection was made for the models, which were used with their default values. The starting set of features used for this step is the union of all the features that at least were found significant in one of the three criteria exposed in the previous sections. The following image shows the confusion matrix of the resulting best model that was found.

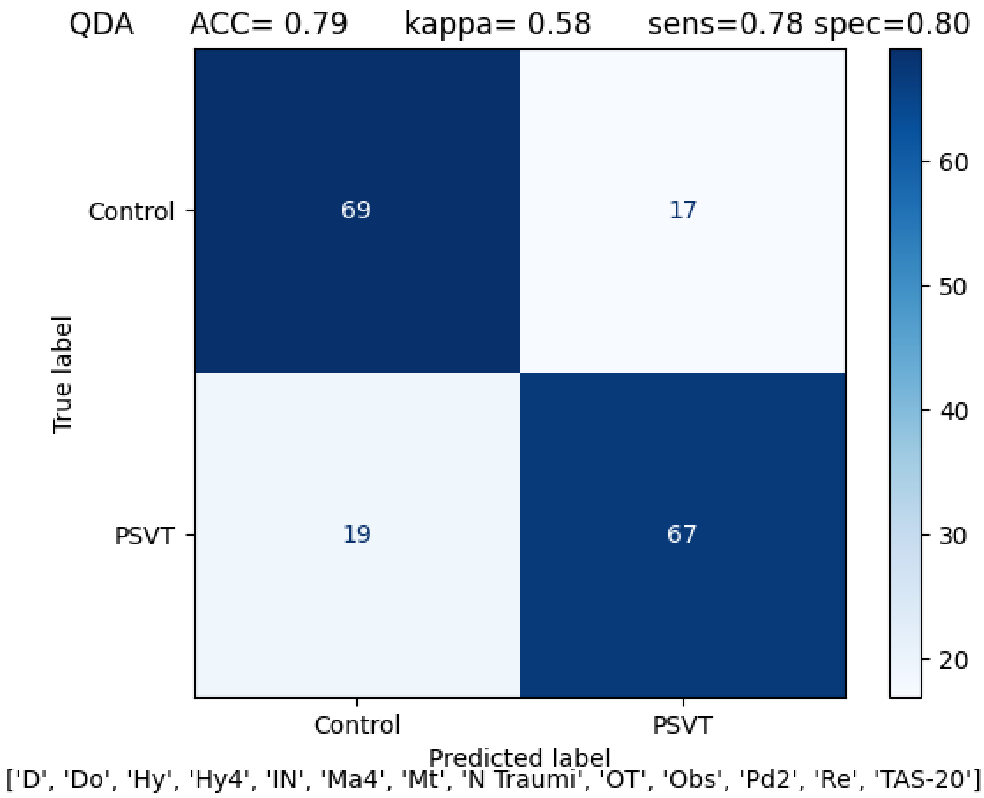


Figure 1: Confusion Matrix of best model obtained with Sequential Feature Selector

This model was found with the floating variant and in Backward mode. The following table shows the order of the selected features in this model

Feature	Sequential Feature Selector Rank
Hy	1
IN	2
Re	3
Hy4	4
Pd2	5
OT	6
N Traumi	7
Obs	8
TAS-20	9

Mt	10
D	11
Ma4	12
Do	13

Table 11: Sequential Feature Selector, Best features

To test the reliability of the model found, the ROC curves over different cross validation folds were computed. The following plot shows these performances.

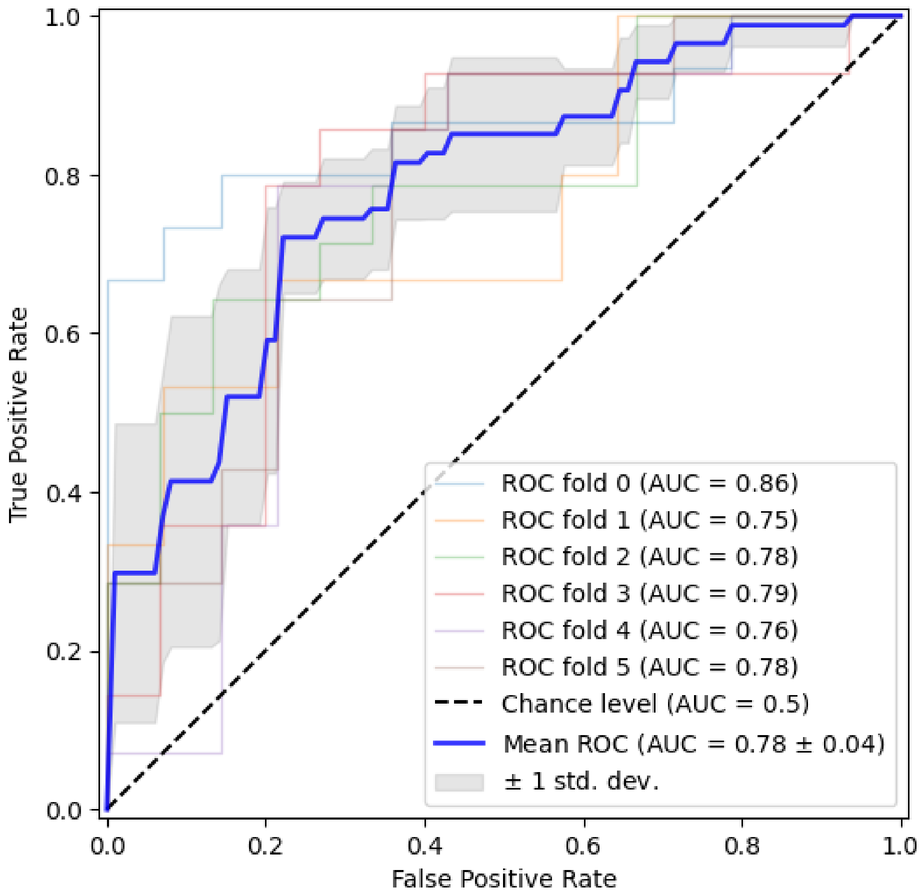


Figure 2: ROC curves for best model found with Sequential Feature Selector

From this plot we can have a confirmation that our model predicts the PSVT better than chance, reaching a mean Area Under the Curve of 0.78.

2.3.5 Factor Analysis

Factor Analysis is a statistical method used to identify underlying relationships between variables. It is widely used in psychology, among the other fields, to reduce data dimensionality and to uncover latent relationships that explain observed data patterns. There are two kinds of Factor Analysis: Explanatory Factor Analysis, which is used to explore data and identify factors without a predetermined idea, and Confirmatory Factor Analysis, used to test hypothesis and theories. [30]

In this work, it has been chosen to conduct an exploratory analysis to find relevant patterns and factors in our data. The 'Statistical Package for Social Science'(SPSS), developed by IBM, was the software used. The factors were extracted using Principal Component Analysis and, after the extraction, it was applied a Promax with Kaiser Normalization as a rotation method, that converged in 18 steps. In the following table, are presented the 7 most significant factors found along with the name chosen for each of them.

Factor Name	Feature	Loading Factor
Emotional Alienation and Distress	Sc4	1.034
	D4	0.982
	Sc2	0.888
	D1	0.887
	Sc3	0.851
	Pt	0.838
	Pd5	0.811
	Sc	0.763

	D2	0.755
	Mt	0.754
	Dep	0.739
	D5	0.728
	D	0.727
	A	0.713
Social Sensitivity and Alienation	Hy1	-0.935
	Pd3	-0.884
	Si1	0.878
	Ma3	-0.823
Interpersonal Detachment and Cynicism	Pa3	-1.078
	Cyn	0.871
	Hy2	-0.841
Health Preoccupation and Somatic Distress	Hs	0.839
	D3	0.795
	Hy	0.776
	Hy4	0.762
	Hea	0.752
Heightened Social and Physical Activation	Ma2	1.023
	Ma	0.923
	Ma4	0.73
Emotional Expression Impairment	TAS-20	0.925
	DDF	0.808
	DIF	0.761
Authority Resistance	Pd2	0.99

Table 12: Results of Factor Analysis

Explanation of the factors found

Factor 1-"Emotional Alienation and Distress"

In the first factor, it is worth noting the predominance of 7 scales: Sc (Schizophrenia), D (Depression), Pt (Psychasthenia), Pd (Psychopathic Deviate), Dep (depression, in a broader way), Mt (Mental Health Awareness) and A(Anxiety). High and positive loading factors for features like Sc4(Alienation or self-alienation), Sc2(Emotional alienation), Pd5(Social Alienation subscale of

Psychopathic Deviate) contributed to the 'Emotional Alienation' part of the name. Since other features refer to depression-related symptoms (D1, D2,D4,D5,Dep), anxiety (Pt ,A), and psychological distress in general(Mt,Sc3) it was chosen the name of "Emotional Alienation and Distress". [27]

Factor 2-"Social Sensitivity and Alienation"

Since we have high negative loading factors for Hy1 and Ma3, we can deduce the presence of sensitivity to social stress in this factor. In fact, low values for both sub-scales indicate respectively anxiety or discomfort in social situations and low imperturbability and indifference to social pressure. On the other hand, High Pd3 and low Si1 indicate social discomfort and introversion. For these reasons, the name "Social Sensitivity and Alienation" was chosen. [27]

Factor 3-'Interpersonal Detachment and Cynicism'

High values of Cyn(Cynicism) and low values of Pa3(Lack of Acceptance of Authority, Paranoia subscale) and Hy2(Need for Affection, Hysteria subscale) suggested the name 'Interpersonal Detachment and Cynicism'. [27]

Factor 4 "Health Preoccupation and Somatic Distress"

The presence of health-related preoccupancy and somatic symptoms is spotted in this factor. It is represented by high scores in subscales that reflect both the mental and physical elements of the distress pattern. In fact, Hs(Hypochondriasis), D3 (Depression Subscale, Mental Dullness), Hy(Hysteria), Hea(Health Concerns) and Hy4(Somatic Complaints, subscale of Hysteria) and Hea(Health concerns) have high loading factors. [27]

Factor 5 “Heightened Social and Physical Activation”

This name captures the elements of high energy and social confidence, identified by high values of Ma4 (Imperturbability), and physical or mental agitation identified by high Ma (Hypomania) and Ma2 (Psychomotor Acceleration). [27]

Factor 6 "Emotional Expression Impairment"

These scales are from TAS-20. High values suggest difficulties in emotional expression and awareness. [20]

Factor 7 "Authority Resistance"

Pd2 indicates difficulties with authority figures. Since high values indicate rebellious attitudes, the name was chosen. [27]

Factor means across PSVT and Control groups

The following plot shows the means of the 7 identified factors across the two groups.

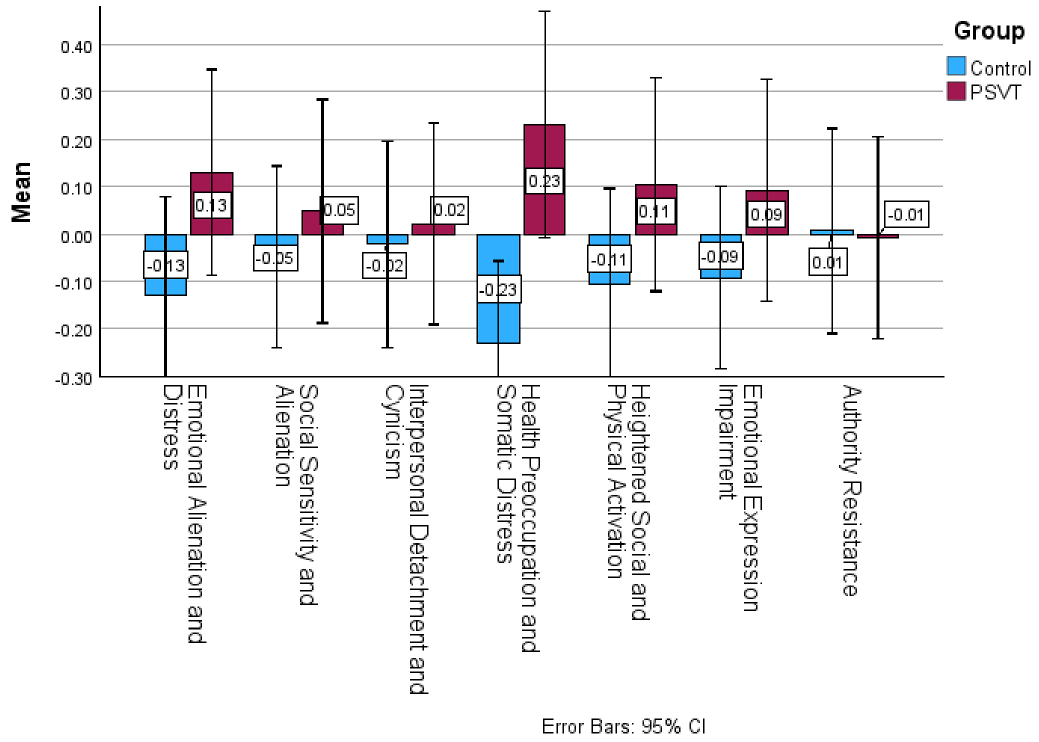


Figure 3:Means of the factors in PSVT and Control groups

2.3.6 Explainable AI Techniques with SHAP

SHAP (Shapley Additive Explanations) is a common method for Explainable AI. It provides a way of describing an output produced by a model, quantifying the contribution of each feature. The advantage of this model is that it does not depend on the machine learning model used with, since it works with models of any kind and type.[32]

Additionally, SHAP provides also a reliable way to perform feature selection. [33]

In this work, the SHAP values were used for both feature selection and to determine the contribution of the features in the models found. Starting from the list of features selected by the statistical criteria, SHAP values were calculated for all features on all models considered. Then the various models were tested first on the first feature, then on the first two, until covering the entire set, in the order given by the contributions according to the SHAP values.

The following table shows the features found in the best model, along with the corresponding SHAP values.

Rank	**Feature**	**Importance**
1	Hy4	0.008936
2	D3	0.006667
3	Hs	0.006057
4	Frs	0.005193
5	IN	0.005117
6	Ma1	0.005053
7	DIF	0.003929
8	DDF	0.003482
9	Es	0.003479
10	Hea	0.003291
11	Pd2	0.003250
12	PO	0.002994
13	Gm	0.002908
14	Mt	0.002898
15	Ma4	0.002878
16	D	0.002790
17	Hy3	0.002760

Table 13: Best Features found with SHAP

For this model it was found an accuracy of 82% in predicting the PSVT outcome, a Cohen's Kappa of 0.66 and a recall of 0.88.

2.4 Discussion of Results for PSVT study

2.4.1 Summary of results and observations

Analyzing the 10 most relevant features obtained by the paired t-test method, we can see that 9 out of 10 belong to two scales: MMPI-2 and MHLC. In particular 6 features from MMPI-2(Hs, Hy4, Hea, Gm, Anx, Frs in order of importance) and three from MHLC (OT, PO, IN) are found. The only exception in the top 10 is ORTRAS, belonging to COPE.

This result suggests that the hypothesis that MMPI-2 and MHLC are more determinant for the presence of PSVT than COPE and TAS-20. This Hypothesis is supported by Cohen's D results, which for the first 10 most significant values suggest the same subscales as MMPI-2 and MHLC. For this method even the top 10 come only from MMPI-2 and MHLC.

The features found through the sequential feature selector also go in this direction, as they come mainly from these two scales, except for N Trauma and Tas-20.

The model found with SHAP partially confirms the hypothesis, even if two features from TAS-20 (DIF and DDF) are selected from it.

In the factor analysis, finally, the top 5 five latent factors found in the data regard MHLC, paying special attention to the factor named ‘Health Concern and Somatic Distress,’ formed by Hs, D3, Hy, Hy4 and Hea. In fact, significantly higher values of these subscales are found in PSVT patients. At the same time, the mean of this factor is significantly higher for PSVT patients, as can be seen in Figure 3.

2.4.2 Psychological risk factors associated with PSVT

Our results highlight that MMPI-2 and MHLC are paramount for predicting PSVT. Concerning MMPI-2, the scales formed by Hs, Hy4, Hea, Gm, Anx, Frs, Hy, D3 are the most significant. For all these sub-scales, patients in the PSVT group have higher values except for D3. The results on this scale suggest that PSVT patients tend to be hypochondriacs and worried about their health (Hs, Hea), to have a psychological block that leads them to be less mentally efficient (D3), a greater tendency to hysteria and manifestations of somatic symptoms (Hy and Hy4) and a major development of anxieties and phobias (Anx, Frs).

Regarding the MHLC, the picture that can be deduced is that the PSVT patient believes that his health depends less on his own personal actions and himself (lower IN values) and more on doctors and health professionals (higher PO values) and other people in general such as friends, family or community (OT).

2.4.3 Best models for predicting PSVT

Support Vector Machines and Quadratic Discriminant Analysis were the two models that achieved best performance among the ones that have been tried. These models performed better than the tested ones with a linear decision function. These results highlight that a nonlinear decision function is necessary to predict the presence of the disease with acceptable results.

2.4.4 Limitations and improvements for future studies.

The results obtained are significant and go in a common direction. However, some limitations that have been encountered and improvements to be considered for the future must be considered.

A structural limitation is given by the dataset, too small for the number of features collected and which makes the basic problem ill-conditioned. In this regard, the collection of a larger sample of data is postponed to future work.

Furthermore, only a part of the possible models was tested and with only their default hyperparameters. Better results could be found by first performing a selection of the hyperparameters with cross validation techniques. Finally, other feature selection techniques and metrics can be evaluated for the choice of a better model.

3.Body Image

In this second project, the aim was to develop a model capable of simulating the evolution of psychological distress related to body image by considering the mutual influence of societal pressures, internalization of an ideal and the actual body mass index. Initially, the psychological measures used for the project are introduced, followed by a review of the methods and a discussion of the results found.

3.1 Psychological Scales for the Body Image Study

3.1.1 The Eating Disorders Examination Questionnaire

The Eating Disorders Examination Questionnaire (EDE-Q) is a psychological scale used to search for behaviors found in an eating disorder. This is done through a 28-item self-report questionnaire. Within it, the scale is divided into 4 sub-scales, each on a sub-theme regarding behaviors and concerns about the body. The subscales in question are called Restraint, Eating Concern, Shape Concern and Weight Concern. [34].

3.1.2 Body Shape Questionnaire

The Body Shape Questionnaire (BSQ) consists of 34 items assessing concerns related to body shape, dissatisfaction with appearance, and fear of gaining weight[35]. Participants rate each item using a 6-point Likert scale (1 = never, 6 = always), reflecting how frequently they experience body image concerns. Shorter versions, such as the BSQ-16 or BSQ-8, are also available for quicker assessments while maintaining strong psychometric properties. [36]

3.1.3 Sociocultural Attitudes Towards Appearance Questionnaire-4

The SATAQ-4 is a psychological measure used to identify the influence of social and media pressures on an individual's body image and idealization. [37]

It consists of 22 items and is one of the many revisions of the original SATAQ [38].

SATAQ-4 consists of 5 subscales: two that indicate how much an individual has internalized a certain type of body image ideal (Thin/Low Body Fat and Muscular/Athletic) and three that give a measure of the pressures a person has socially related to the body (Family, Peers and Media) [37].

3.2 Methods and Results for Body Image study

3.2.1 Definition of PSYCH- Attitudinal component of Body Image

As a first step of this project part, it was necessary to obtain a one-dimensional variable summarizing the results of the various psychological scales submitted to the patients: the 4 sub-scales of EDE-Q and BSQ.

To do this, PSYCH was defined as the first dimension obtained by applying Principal component analysis to the data.

This latent variable is also defined in other studies prior to this work through the same procedure. [14][16] For example, Irivine et Al. in 2020 wrote:

"High scores on this latent variable, henceforth referred to as PSYCH, reflect a combination of high body image concerns, pathological attitudes to eating, low self-esteem, and depressed mood. Low scores reflect the opposite; confidence in one's body, the absence of eating pathology, high self-esteem, and the absence of depressive thoughts."[16]

3.2.2 Definition of other Variables of the model

Since the goal of the research was to capture the mutual influences of the attitudinal component of body image, its perceptual component, the internalization of the ideal body image and the societal influence, appropriate variables needed to be declared.

As said in the previous paragraph, **PSYCH** represents the attitudinal component of the body image. It represents how a person feels about his or her body and the amount of presence of depressive thoughts. In our work, it is expressed in terms of factor scores.

On the other hand, the perceptional component is represented by the **Estimated Body Mass Index.** This variable represents an estimate of how a person perceives his or her body. Expressed in terms of Body Mass Index, the estimate is calculated by the model through linear regression.

To also consider the internalized ideal in the individual, an **Ideal Body Mass Index** was also estimated in the model.

Regarding the societal influence, scorings of SATAQ-4 questionnaire are used for the scope. Additionally, it is important noting that this variable was split into two parts: **SATAQta**, average of thinness and athleticism scores, and **SATAQfpm**, mean of the family, peer and media pressures.

Finally, **Age** and the **actual Body Mass Index** were the other two variables considered in the model.

In the following lines, it is reported the definition of Body Mass Index taken from Wikipedia's site:

"Body mass index (BMI) is a value derived from the mass (weight) and height of a person. The BMI is defined as the body mass divided by the square of the body height, and is expressed in units of kg/m^2, resulting from mass in kilograms (kg) and height in meters (m)." [39]

The following table shows the statistics of the data collected[1] :

	Mean	Std	Min	Max	N
BMI_self	27.54	6.85	15.86	43.93	330.00
BMI_ideal	20.95	3.34	14.28	38.58	330.00
BMI_diff	6.59	5.84	-4.66	25.99	330.00
Age	36.08	11.33	16.00	64.00	330.00
BMI	25.87	5.48	15.99	46.23	330.00
SATAQta	2.65	0.97	1.00	5.00	279.00
SATAQfpm	2.34	0.87	1.00	4.67	279.00
psych	0.00	1.00	-1.41	2.55	330.00

Table 14:Mean, Standard Deviation, Minimum, Maximum and total number of samples for data collected in the BMI project

[1] The data analyzed in this study were collected by Piers Cornellisen, an external researcher, and provided by the supervisor, Vito De Feo, for the analysis.

3.2.3 The baseline of the model: the three linear regression equations

With the aim of studying the mutual influence of the variables under consideration, three linear regression equations were created based on the data collected.

A. Estimated BMI in terms of Age, Actual BMI, PSYCH and SATAQta:

   The obtained equation is the following:

   A: $Self\_estimated\_BMI = 3.52 + 0.107 * Age + 0.861 * actual\ BMI + 1.622 * PSYCH - 0.785 * SATAQta$

   The obtained coefficient of determination for this equation amounts to 0.77, indicating that the observed results were replicated quite well by the model. Therefore, a minor disturbance was added to the implementation in MATLAB compared to the other equations.

B. Estimated Ideal BMI in terms of Age, Actual BMI, PSYCH and SATAQta:

   The obtained equation is the following:

   B: $Ideal\ BMI = 12.91 + 0.049 * Age + 0.316 * actual\ BMI - 0.752 * PSYCH - 0.698 * SATAQta$

In this case, the coefficient of determination amounts only to 0.77. Therefore, a bigger disturbance was added in the implementation in MATLAB compared to the other equations.

C. <u>PSYCH PREDICTED BY SATAQta, SATAQfpm and BMI difference:</u>

C: $Psych = -2.391 + (0.426 * SATAQta) + (0.336 * SATAQfpm) + (0.0724 * BMI\_diff)$

Where $BMI\_diff = Self - estimated\ BMI - Ideal\ BMI$

The coefficient of determination in this case amounts to 0.67, that makes it quite reliable and with a lower disturbance.

The following diagram shows the structure of the model obtained combining the three equations presented:

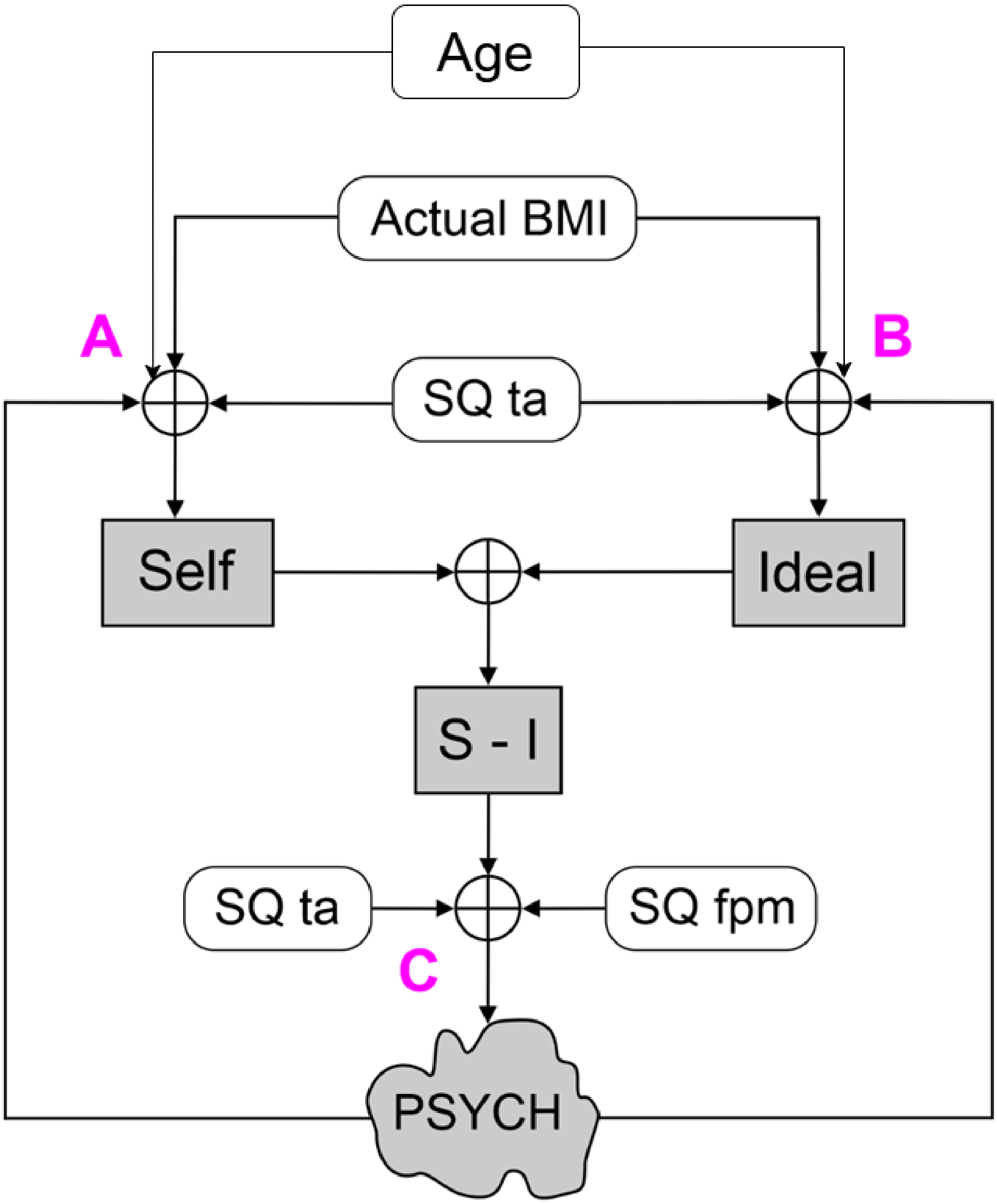


Figure 4: Diagram of the mathematical model for Body Image

This model was implemented in MATLAB- Simulink, an environment useful to analyze the results of the model across different time steps, so that it is possible to simulate the mutual influence of the three variables over the time.

3.2.4 Analysis of the output of the Model

In this section the output of the model was analyzed, focusing on the outcomes of PSYCH as dependent variable. More specifically, special attention was paid to how quickly the model tended to diverge as the values of the variables varied. For this reason, a quantity called "**divergency speed**" was defined, obtained as the inverse of the time it took the model to diverge (i.e., reach the maximum value of PSYCH).

The analysis is divided into three stages: one-dimensional, two-dimensional and three-dimensional.

In the one-dimensional case, one variable was allowed to vary at a time over the range of values in which it was observed, while the others were held constant at their mean values. In contrast, in the two-dimensional case, two variables were varied in their ranges, while in the three-dimensional case all three were varied.

When the variables are kept constant in the analysis, they are set at their mean value, according to Table 1.

3.2.4.1 One-dimensional analysis

In the following tables for the one-dimensional analysis, 'Divergent' is a flag that is set to 1 if the model diverges (i.e. PSYCH reaches its Maximum value), while 'D_time' indicates the instant in which PSYCH reaches its Maximum value. 'EST_BMI', 'IDEAL_BMI' and 'Delta_BMI' are the respectively the estimated Body Mass Index, the ideal Body mass index and the difference between the two. Actual_BMI is the real individual's body mass index.

Varying Actual BMI and keeping other independent values at their mean:

Actual_BMI	Divergent	D_time	EST_BMI	IDEAL_BMI	Delta_BMI
15.99	0	Inf	17.869	17.869	0
16.49	0	Inf	18.027	18.027	0
16.99	0	Inf	18.185	18.185	0
17.49	0	Inf	18.592	18.592	0
17.99	0	Inf	18.955	18.955	0
18.49	0	Inf	19.193	19.193	0
18.99	0	Inf	19.613	19.613	0
19.49	0	Inf	20.043	20.043	0
19.99	0	Inf	20.474	20.474	0
20.49	0	Inf	20.904	20.826	0.07814
20.99	0	Inf	21.335	20.984	0.35064
21.49	0	Inf	21.765	21.142	0.62314
21.99	0	Inf	22.196	21.3	0.89564
22.49	0	Inf	22.626	21.458	1.1681
22.99	0	Inf	23.057	21.616	1.4406
23.49	0	Inf	23.487	21.774	1.7131
23.99	0	Inf	23.918	21.932	1.9856

24.49	0	Inf	24.348	22.09	2.2581
24.99	0	Inf	24.779	22.248	2.5306
25.49	0	Inf	25.209	22.406	2.8031
25.99	1	25.454	32.267	19.22	13.046
26.49	1	17.063	32.543	19.224	13.319
26.99	1	14.021	33.14	19.549	13.591
27.49	1	12.142	33.313	19.449	13.864
27.99	1	10.84	33.745	19.609	14.136
28.49	1	9.8393	33.929	19.52	14.409
28.99	1	9.0172	34.45	19.769	14.681
29.49	1	8.366	35.284	20.33	14.954
29.99	1	7.8137	35.853	20.627	15.226
30.49	1	7.3509	36.605	21.106	15.499
30.99	1	6.9284	36.481	20.709	15.771
31.49	1	6.5499	37.267	21.223	16.044
31.99	1	6.219	37.416	21.1	16.316
32.49	1	5.9377	37.812	21.223	16.589
32.99	1	5.6712	37.959	21.097	16.861
33.49	1	5.4305	38.884	21.75	17.134
33.99	1	5.2111	39.071	21.665	17.406
34.49	1	4.993	39.42	21.741	17.679
34.99	1	4.8071	39.798	21.846	17.951
35.49	1	4.6351	40.528	22.304	18.224
35.99	1	4.4773	41.035	22.538	18.496

36.49	1	4.3317	41.089	22.32	18.769
36.99	1	4.1891	41.121	22.08	19.041
37.49	1	4.0551	41.873	22.559	19.314
37.99	1	3.9347	42.628	23.041	19.586
38.49	1	3.821	42.772	22.913	19.859
38.99	1	3.7105	42.941	22.81	20.131
39.49	1	3.6076	43.466	23.062	20.404
39.99	1	3.5188	44	23.747	20.253
40.49	1	3.4317	44	24.271	19.729
40.99	1	3.3654	44	23.352	20.648
41.49	1	3.3083	44	23.51	20.49
41.99	1	3.26	44	23.992	20.008
42.49	1	3.2251	44	24.15	19.85
42.99	1	3.2031	44	24.308	19.692
43.49	1	3.1972	44	24.395	19.605
43.99	1	3.2104	44	24.624	19.376
44.49	1	3.2393	44	24.782	19.218
44.99	1	3.2791	44	24.94	19.06
45.49	1	3.3258	44	24.774	19.226
45.99	1	3.3741	44	24.932	19.068

Table 15: Divergency Table for Actual BMI

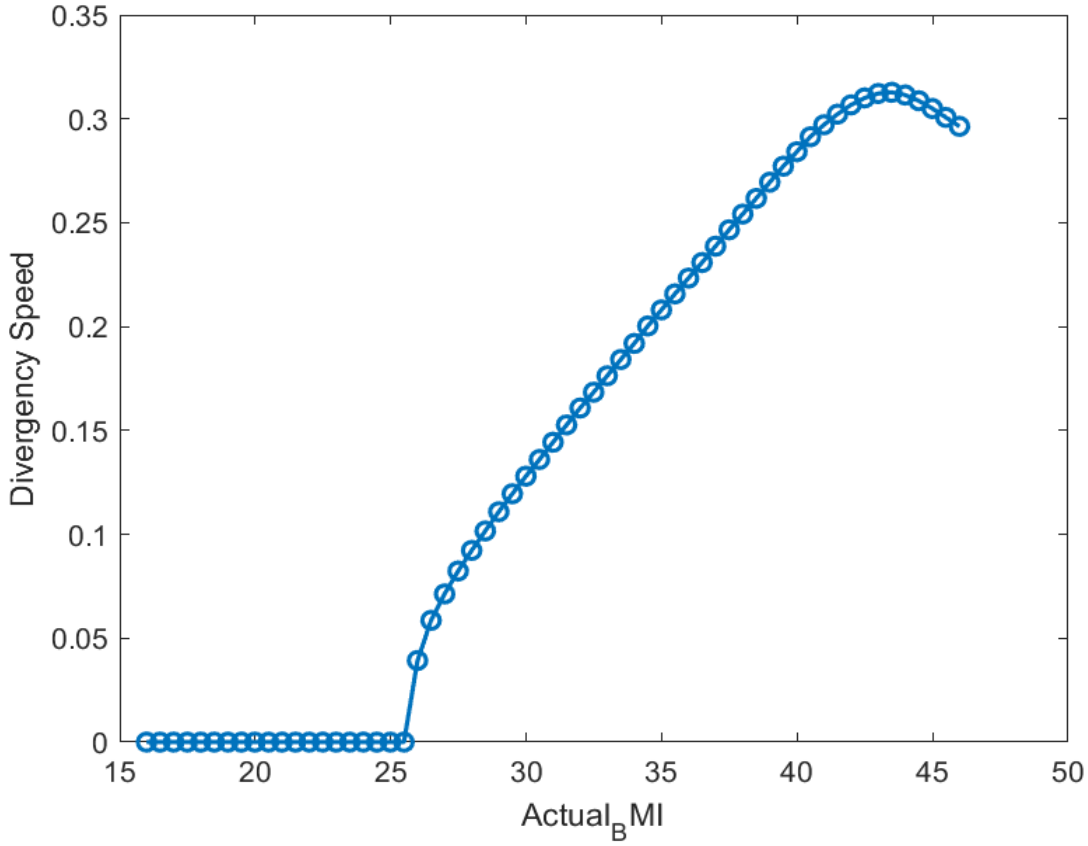


Figure 5: Divergency Speed for Actual BMI

<u>Varying SATAQfpm and keeping other independent values at their mean</u>

SATAQfpm	**Divergent**	**D-time**	**EST_BMI**	**IDEAL_BMI**	**Delta_BMI**
1	0	Inf	25.536	22.526	3.0102
1.05	0	Inf	25.536	22.526	3.0102
1.1	0	Inf	25.536	22.526	3.0102
1.15	0	Inf	25.536	22.526	3.0102
1.2	0	Inf	25.536	22.526	3.0102
1.25	0	Inf	25.536	22.526	3.0102

1.3	0	Inf	25.536	22.526	3.0102
1.35	0	Inf	25.536	22.526	3.0102
1.4	0	Inf	25.536	22.526	3.0102
1.45	0	Inf	25.536	22.526	3.0102
1.5	0	Inf	25.536	22.526	3.0102
1.55	0	Inf	25.536	22.526	3.0102
1.6	0	Inf	25.536	22.526	3.0102
1.65	0	Inf	25.536	22.526	3.0102
1.7	0	Inf	25.536	22.526	3.0102
1.75	0	Inf	25.536	22.526	3.0102
1.8	0	Inf	25.536	22.526	3.0102
1.85	0	Inf	25.536	22.526	3.0102
1.9	0	Inf	25.536	22.526	3.0102
1.95	0	Inf	25.536	22.526	3.0102
2	0	Inf	25.536	22.526	3.0102
2.05	0	Inf	25.536	22.526	3.0102
2.1	0	Inf	25.536	22.526	3.0102
2.15	0	Inf	25.536	22.526	3.0102
2.2	0	Inf	25.536	22.526	3.0102
2.25	0	Inf	25.536	22.526	3.0102
2.3	0	Inf	25.536	22.526	3.0102
2.35	1	26.976	31.75	18.769	12.981
2.4	1	18.089	31.835	18.854	12.981
2.45	1	14.926	31.957	18.976	12.981

2.5	1	13.018	31.916	18.935	12.981
2.55	1	11.67	31.196	18.215	12.981
2.6	1	10.637	32.516	19.535	12.981
2.65	1	9.8023	31.673	18.692	12.981
2.7	1	9.0998	31.764	18.783	12.981
2.75	1	8.5253	31.509	18.528	12.981
2.8	1	8.0211	32.193	19.212	12.981
2.85	1	7.6025	32.932	19.95	12.981
2.9	1	7.2268	32.131	19.15	12.981
2.95	1	6.8685	31.48	18.499	12.981
3	1	6.5498	32.428	19.447	12.981
3.05	1	6.2642	32.147	19.166	12.981
3.1	1	6.0201	32.226	19.245	12.981
3.15	1	5.7894	31.785	18.804	12.981
3.2	1	5.5685	31.933	18.952	12.981
3.25	1	5.3727	31.905	18.924	12.981
3.3	1	5.187	31.236	18.255	12.981
3.35	1	5.0006	31.435	18.454	12.981
3.4	1	4.8409	31.945	18.964	12.981
3.45	1	4.6896	32.245	19.264	12.981
3.5	1	4.5524	31.938	18.957	12.981
3.55	1	4.4237	32.321	19.34	12.981
3.6	1	4.3005	31.945	18.964	12.981
3.65	1	4.1793	31.547	18.566	12.981

3.7	1	4.065	31.869	18.887	12.981
3.75	1	3.961	32.192	19.211	12.981
3.8	1	3.8632	31.906	18.925	12.981
3.85	1	3.7678	31.645	18.664	12.981
3.9	1	3.6758	31.739	18.758	12.981
3.95	1	3.5894	32.266	19.285	12.981
4	1	3.5108	32.266	19.285	12.981
4.05	1	3.4377	32.632	19.651	12.981
4.1	1	3.3646	31.555	18.574	12.981
4.15	1	3.2912	31.879	18.898	12.981
4.2	1	3.2229	31.879	18.898	12.981
4.25	1	3.1571	31.808	18.827	12.981
4.3	1	3.0939	31.768	18.787	12.981
4.35	1	3.033	31.768	18.787	12.981
4.4	1	2.9751	32.06	19.079	12.981
4.45	1	2.9202	32.06	19.079	12.981
4.5	1	2.8678	32.197	19.216	12.981
4.55	1	2.8174	32.197	19.216	12.981
4.6	1	2.7692	32.358	19.377	12.981
4.65	1	2.7229	32.358	19.377	12.981

Table 16: Divergency Table for SATAQfpm

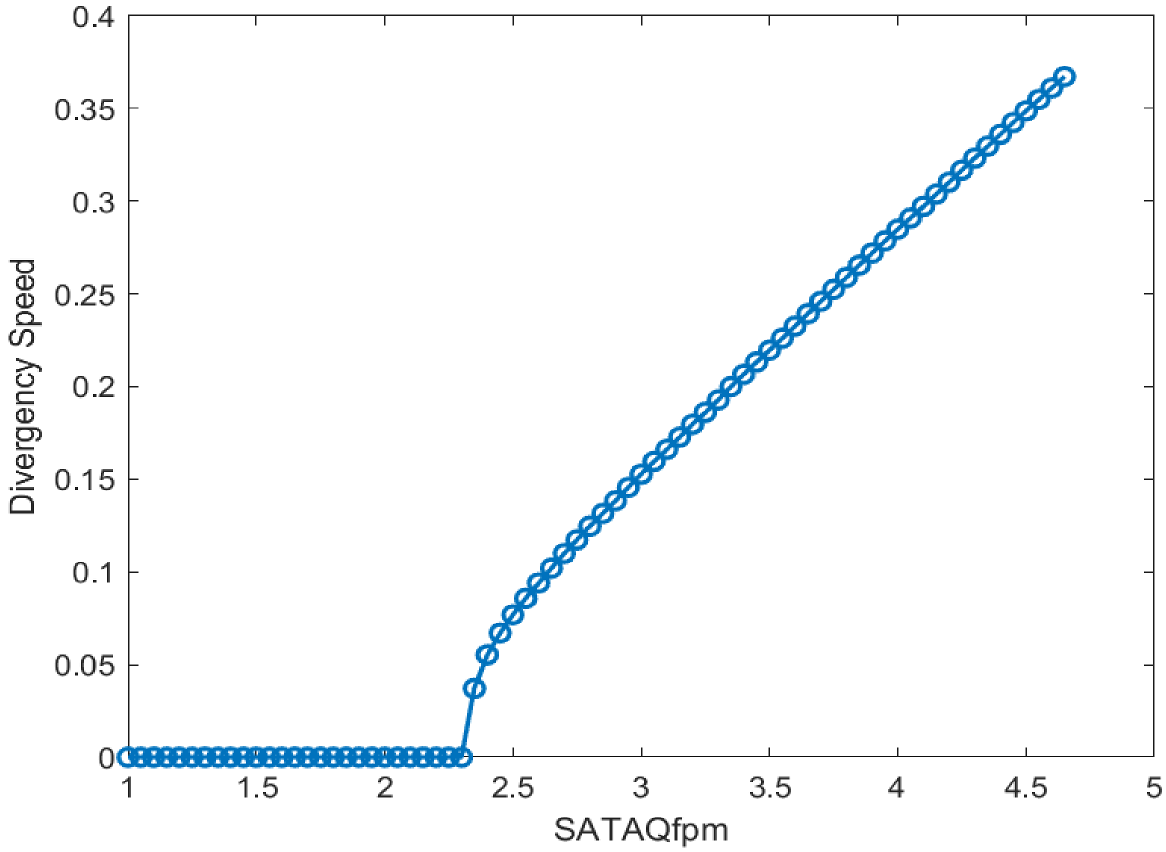


Figure 6: Divergency speed for SATAQfpm

<u>Varying SATAQta and keeping other values constant</u>

SATAQta	**Divergent**	**D-time**	**EST_BMI**	**IDEAL_BMI**	**Delta_BMI**
1	0	Inf	26.832	23.678	3.1538
1.05	0	Inf	26.792	23.643	3.1494
1.1	0	Inf	26.753	23.608	3.1451
1.15	0	Inf	26.714	23.573	3.1407
1.2	0	Inf	26.675	23.538	3.1364
1.25	0	Inf	26.635	23.503	3.132
1.3	0	Inf	26.596	23.468	3.1277

1.35	0	Inf	26.557	23.434	3.1233
1.4	0	Inf	26.518	23.399	3.119
1.45	0	Inf	26.478	23.364	3.1146
1.5	0	Inf	26.439	23.329	3.1103
1.55	0	Inf	26.4	23.294	3.1059
1.6	0	Inf	26.361	23.259	3.1016
1.65	0	Inf	26.321	23.224	3.0972
1.7	0	Inf	26.282	23.189	3.0929
1.75	0	Inf	26.243	23.154	3.0885
1.8	0	Inf	26.204	23.119	3.0842
1.85	0	Inf	26.164	23.085	3.0798
1.9	0	Inf	26.125	23.05	3.0755
1.95	0	Inf	26.086	23.015	3.0711
2	0	Inf	26.047	22.98	3.0668
2.05	0	Inf	26.007	22.945	3.0624
2.1	0	Inf	25.968	22.91	3.0581
2.15	0	Inf	25.929	22.875	3.0537
2.2	0	Inf	25.89	22.84	3.0494
2.25	0	Inf	25.85	22.805	3.045
2.3	0	Inf	25.811	22.77	3.0407
2.35	0	Inf	25.772	22.736	3.0363
2.4	0	Inf	25.733	22.701	3.032
2.45	0	Inf	25.693	22.666	3.0276
2.5	0	Inf	25.654	22.631	3.0233

2.55	0	Inf	25.615	22.596	3.0189
2.6	0	Inf	25.576	22.561	3.0146
2.65	1	34.738	31.791	18.81	12.981
2.7	1	17.886	31.935	18.958	12.977
2.75	1	14.276	32.064	19.092	12.972
2.8	1	12.22	31.582	18.614	12.968
2.85	1	10.823	31.763	18.799	12.964
2.9	1	9.7699	32.132	19.173	12.959
2.95	1	8.9096	31.362	18.407	12.955
3	1	8.2413	31.25	18.3	12.951
3.05	1	7.6778	32.618	19.671	12.946
3.1	1	7.2117	31.778	18.836	12.942
3.15	1	6.7692	31.554	18.616	12.938
3.2	1	6.3974	30.981	18.048	12.933
3.25	1	6.0707	31.755	18.826	12.929
3.3	1	5.7805	31.274	18.35	12.924
3.35	1	5.5092	31.384	18.464	12.92
3.4	1	5.2713	31.491	18.576	12.916
3.45	1	5.0388	30.807	17.896	12.911
3.5	1	4.8355	31.278	18.371	12.907
3.55	1	4.6502	31.539	18.636	12.903
3.6	1	4.4818	31.576	18.677	12.898
3.65	1	4.3269	31.16	18.266	12.894
3.7	1	4.1755	30.722	17.833	12.89

3.75	1	4.0349	31.005	18.12	12.885
3.8	1	3.9092	31.29	18.409	12.881
3.85	1	3.7889	30.703	17.826	12.877
3.9	1	3.6733	30.758	17.886	12.872
3.95	1	3.5673	31.246	18.378	12.868
4	1	3.4718	31.573	18.709	12.864
4.05	1	3.3817	30.456	17.597	12.859
4.1	1	3.2895	30.741	17.886	12.855
4.15	1	3.2047	30.702	17.851	12.851
4.2	1	3.1238	30.592	17.745	12.846
4.25	1	3.0467	30.512	17.671	12.842
4.3	1	2.974	30.765	17.927	12.837
4.35	1	2.9058	30.725	17.892	12.833
4.4	1	2.8414	30.824	17.995	12.829
4.45	1	2.7802	30.945	18.121	12.824
4.5	1	2.7221	30.906	18.086	12.82
4.55	1	2.6654	30.486	17.67	12.816
4.6	1	2.6104	30.446	17.635	12.811
4.65	1	2.5591	30.855	18.048	12.807
4.7	1	2.5101	30.816	18.013	12.803
4.75	1	2.4615	30.238	17.439	12.798
4.8	1	2.4144	30.198	17.404	12.794
4.85	1	2.3689	30.071	17.282	12.79
4.9	1	2.325	30.032	17.247	12.785

4.95	1	2.2828	29.996	17.215	12.781
5	1	2.242	29.956	17.18	12.777

Table 17: Divergency Speed for SATAQta

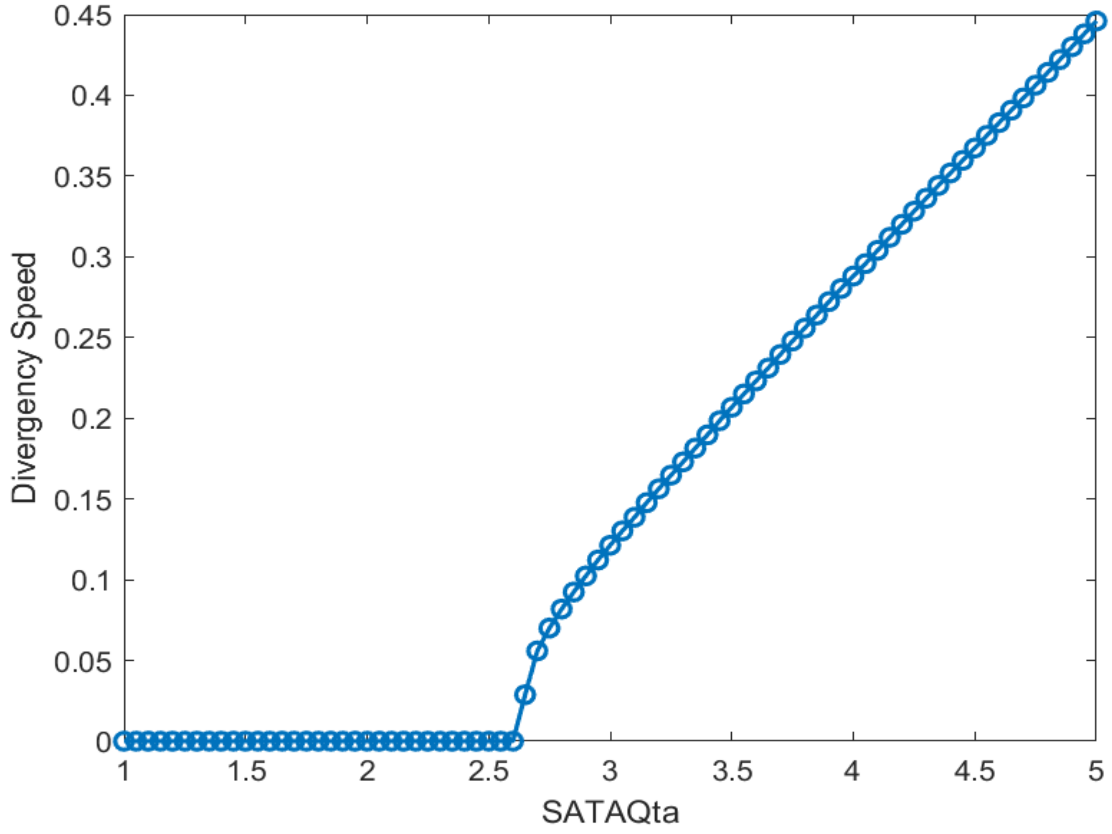


Figure 7: Divergency speed for SATAQta

3.2.4.2 Two-dimensional analysis

In this section, the divergency speed of the model is shown by varying two input variables at a time and holding the others constant at their mean values.

Varying SATAQfpm and Actual BMI

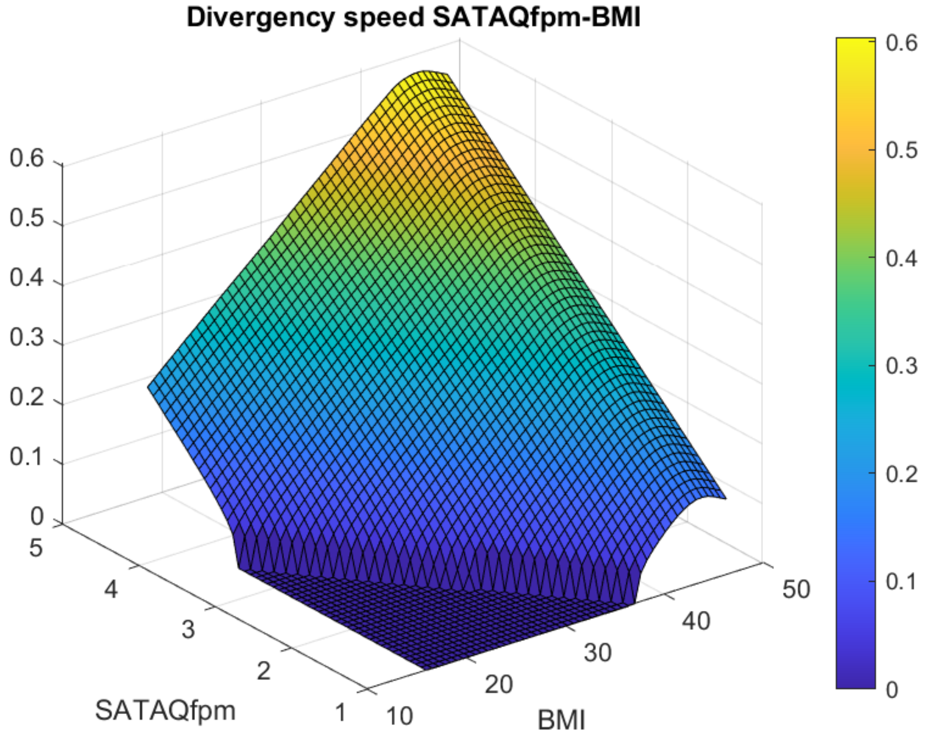


Figure 8: Divergency Speed for SATAQfpm-BMI (3D)

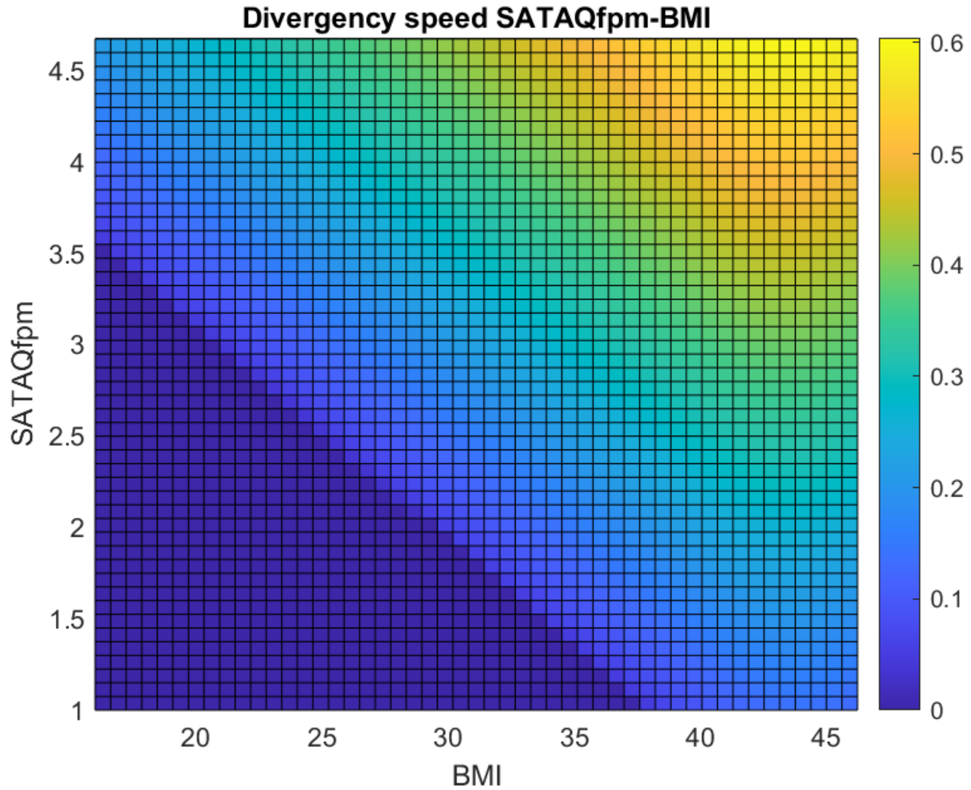


Figure 9: Divergency Speed for SATAQfpm-BMI

Varying SATAQta and Actual BMI

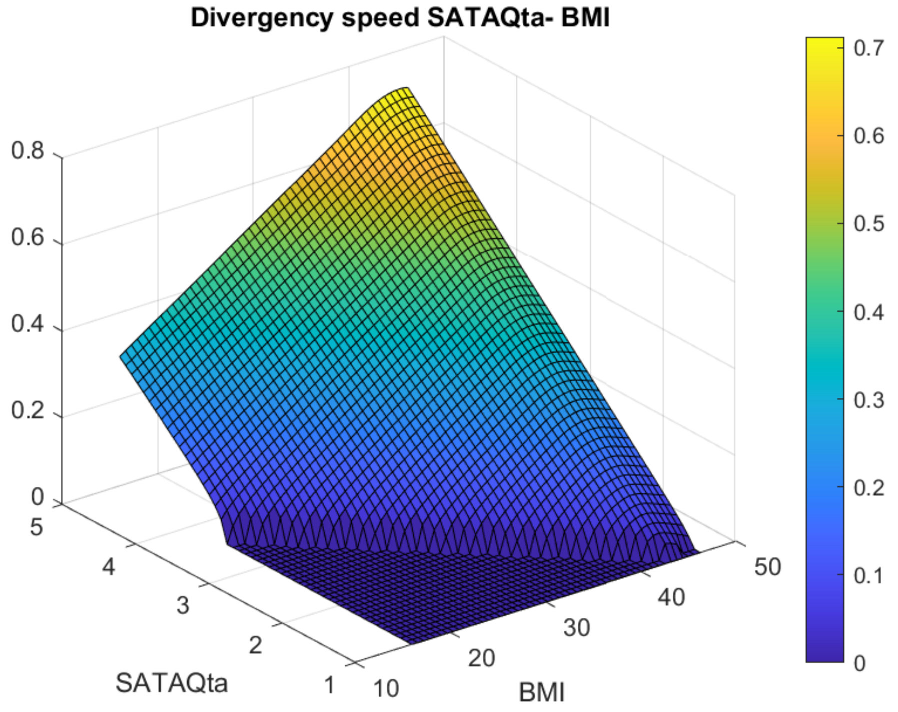


Figure 10: Divergency speed for SATAQta-BMI (3D)

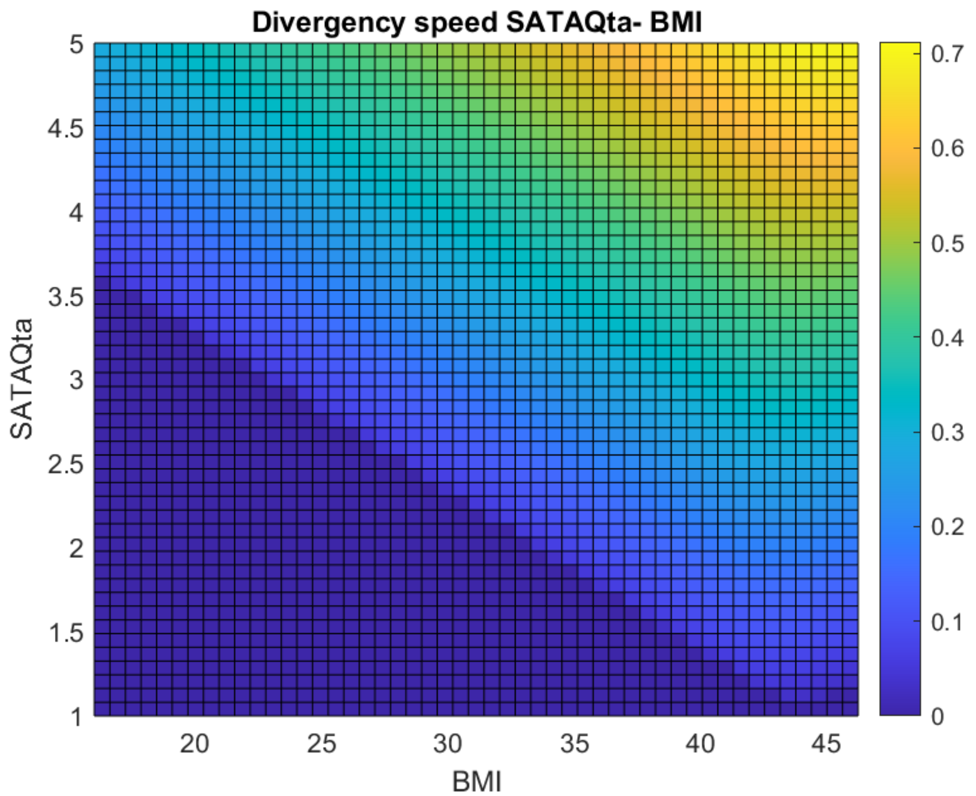


Figure 11: Divergency speed for SATAQta-BMI

Varying SATAQta and SATAQfpm

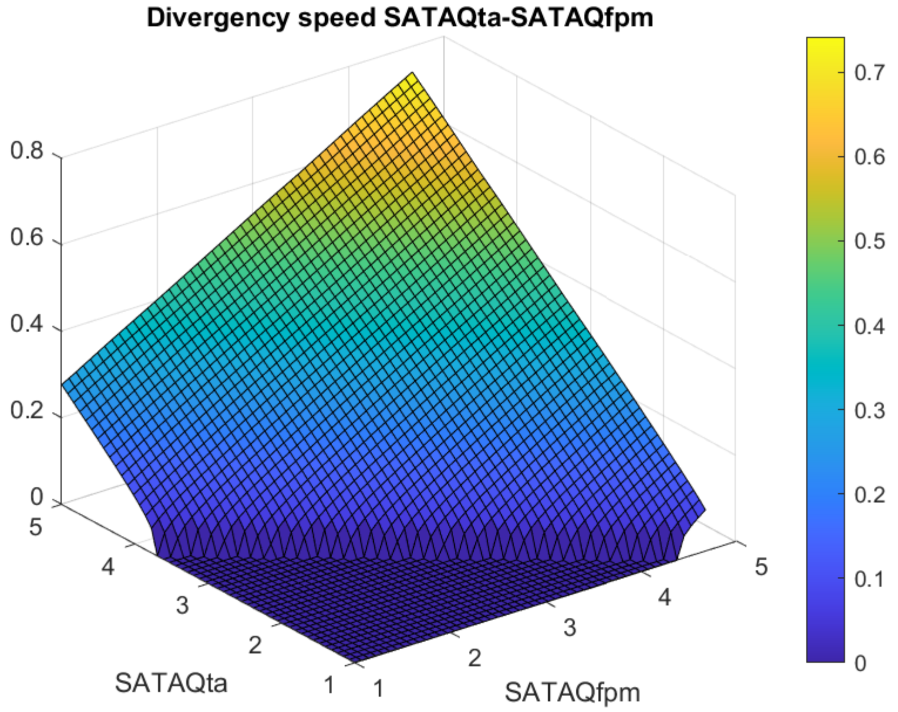


Figure 12: Divergency Speed for SATAQta-SATAQfpm (3D)

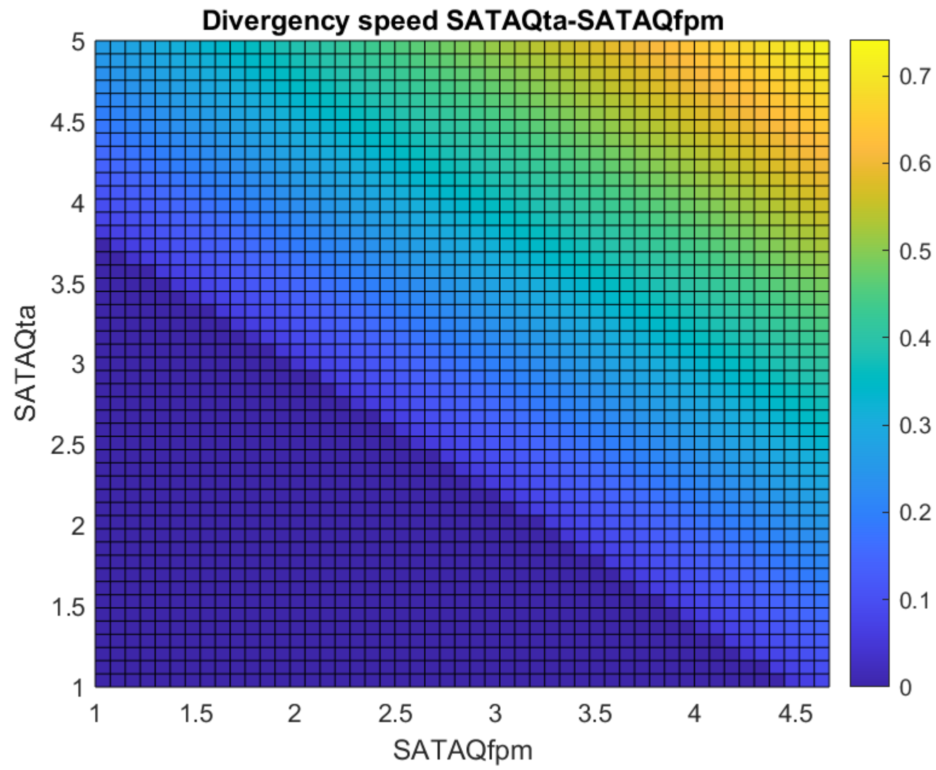
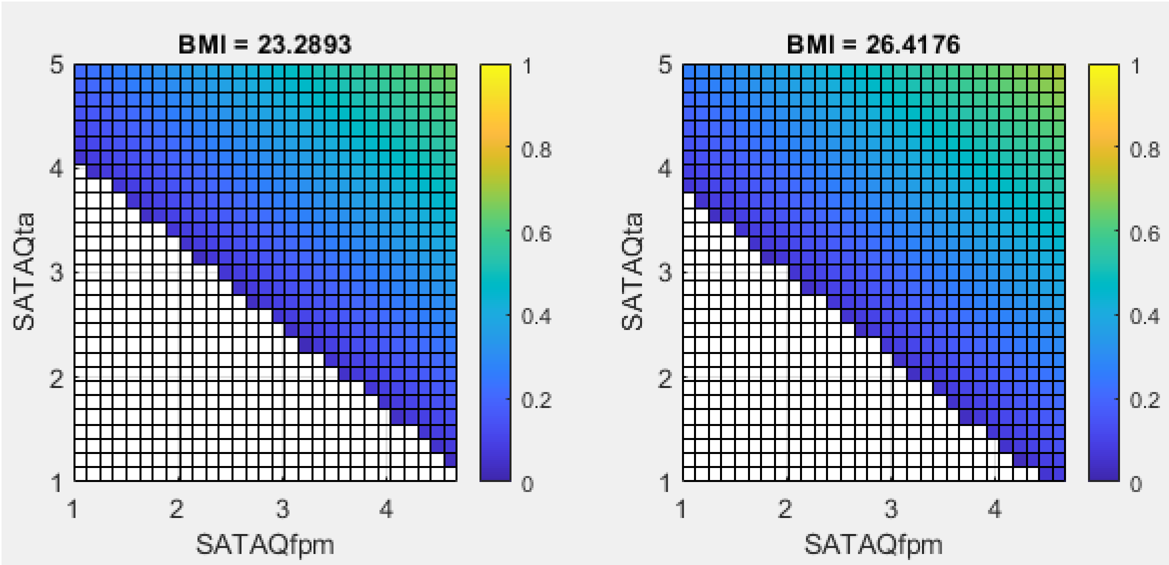
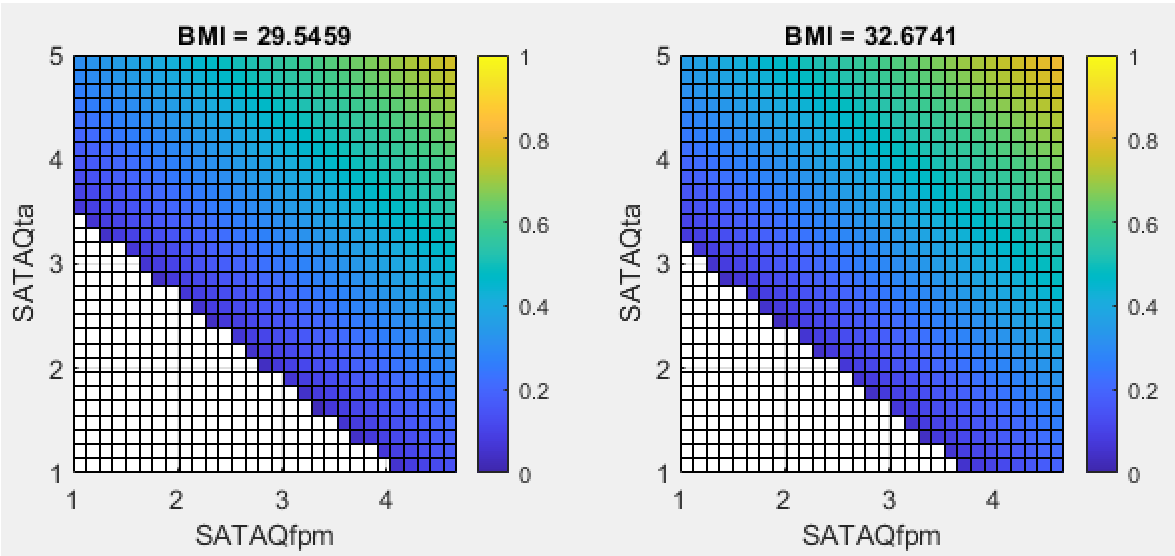


Figure 13: Divergency Speed for SATAQta-SATAQfpm

3.2.4.3 Three-dimensional analysis

The following graphs show model's divergency speed for 8 values of BMI varying SATAQfpm and SATAQta in their intervals.





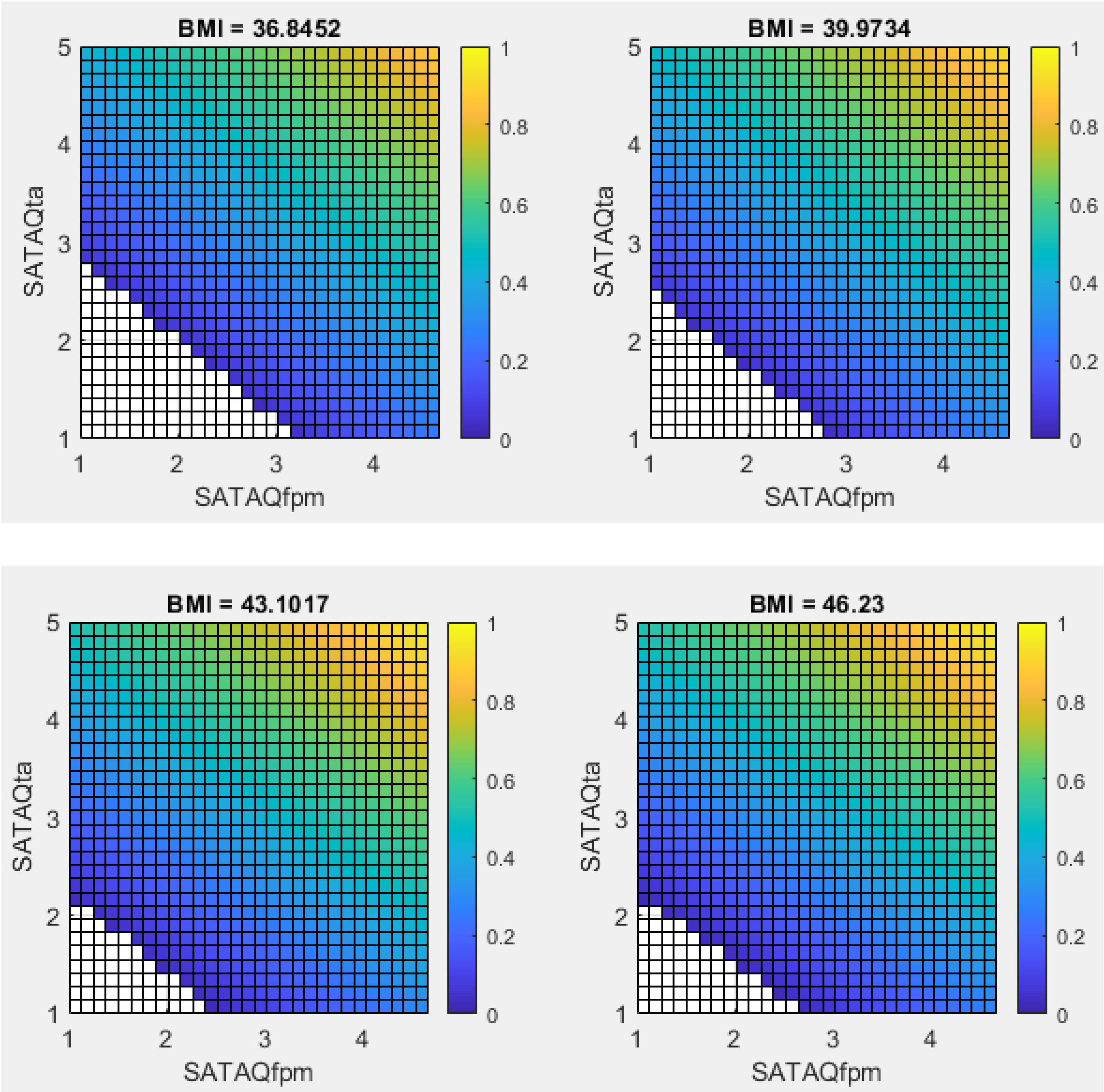


Figure 14: Divergency Speed, for fixed BMI and varying SATAQta and SATAQfpm

It is clear noting from these graphs that how the BMI index increases, the model predicts higher values of PSYCH more quickly, indicating a low attitudinal body Image. These results are coherent to what found in Cornelissen et al. analysis for patients suffering from anorexia spectrum disorders. [14]

This result can be further observed in this 3D plot, where all the three independent variables of the model change in their interval.

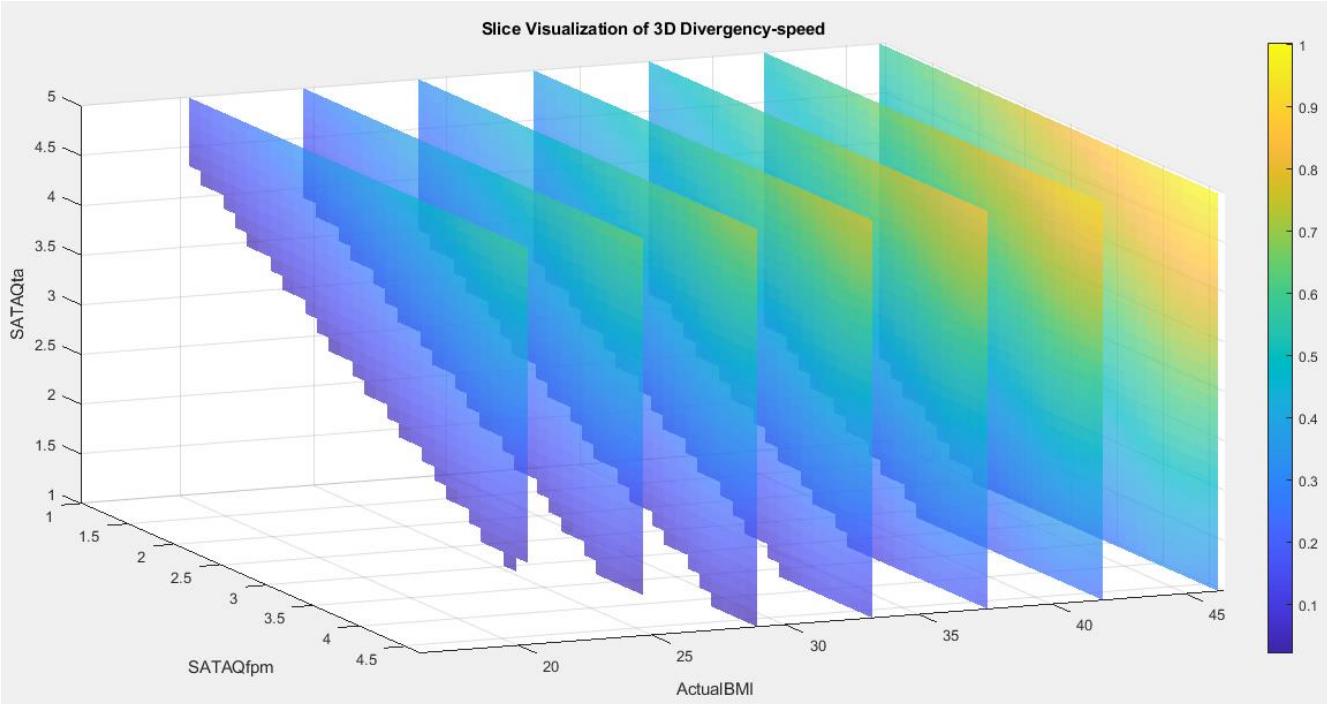


Figure 15: 3D Analysis- Divergency Speed for SATAQta, SATAQfpm and Actual_BMI

3.2.5 Further variations to the mathematical model: from a static to a dynamic model

In this section, improvements and modifications were imported to the model used so far. The goal was to arrive at one that considered the patient's initial PSYCH, that was discrete, so that his time-steps could be interpreted as real periods of time (e.g. months), and that was dynamic.

To get to this end, a new equation was first obtained by rewriting BMI_DIFF as the difference between equations A and B. The resulting equation, which we will denote by D, is the following:

D: $BMI\_diff = -9.39 + 0.058 * Age + 0.545 * actual\ BMI + 2.374 * PSYCH - 0.087 * SATAQta$

Then it was decided to add an initial PSYCH term to equation C, which became as follows:

$$PSYCH = -2.391 + 0.426 * SATAQta + 0.336 * SATAQfpm + 0.0724 * BMI\_diff + PSYCH0$$

Combining the latter with equation D, we finally obtained:

$$PSYCH = -3.70819 + 0.50681 * SATAQta + 0.40574 * SATAQfpm + 0.0050707 * Age + 0.047648 * actual\ BMI + 1.207551 * PSYCH0$$

The latter is a single equation that takes as input the entire patient’s state, including the initial PSYCH0, and returns PSYCH as output. Taking into account the dynamicity of the input variables over time, a discrete-time model was finally obtained that accounts for the evolution of the patients' state over different time steps.

Finally, to have a true dynamic model, it was necessary to consider a source of variation between the generic state PSYCH(n+1) and PSYCH(n). The hypothesis that was considered is that if the difference between the ideal and perceived body mass image is greater than zero then there is a psychological force that tends to make the attitudinal component of body image worse (i.e., make PSYCH increase). Therefore, a component proportional to BMI_diff was considered in PSYCH. The multiplicative coefficient of this component was denoted by beta.

The resulting discrete-time model is the following:

$$
\begin{aligned}
\mathrm{PSYCH}(0) = {} & -3.70819 + 0.50681 * \mathrm{SATAQta}(0) + 0.40574 * \mathrm{SATAQfpm}(0) + \\
& + 0.0050707 * \mathrm{Age}(0) + 0.047648 * \mathrm{actual\ BMI}(0) \\
\mathrm{BMI\_diff}(n) = {} & -9.39 + 0.058 * \mathrm{Age}(n) + 0.545 * \mathrm{actual\ BMI}(n) + \\
& + 2.374 * \mathrm{PSYCH}(n) - 0.087 * \mathrm{SATAQta}(n) \\
\mathrm{PSYCH}(n+1) - \mathrm{PSYCH}(n) = {} & 0.50681 * \left(\mathrm{SATAQta}(n+1) - \mathrm{SATAQta}(n)\right) + \\
& + 0.40574 * \left(\mathrm{SATAQfpm}(n+1) - \mathrm{SATAQfpm}(n)\right) + 0.0050707 * \left(\mathrm{Age}(n+1) - \mathrm{Age}(n)\right. \\
& + 0.047648 * (\mathrm{actual\ BMI}(n+1) - \mathrm{actual\ BMI}(n)) + \mathrm{beta} * \mathrm{BMI\_diff}(n) \\
\mathrm{beta} = 0\ & if\ NOT\ (\mathrm{BMI\_diff}(n) > 0\ and\ PSYCH > -1.5)
\end{aligned}
$$

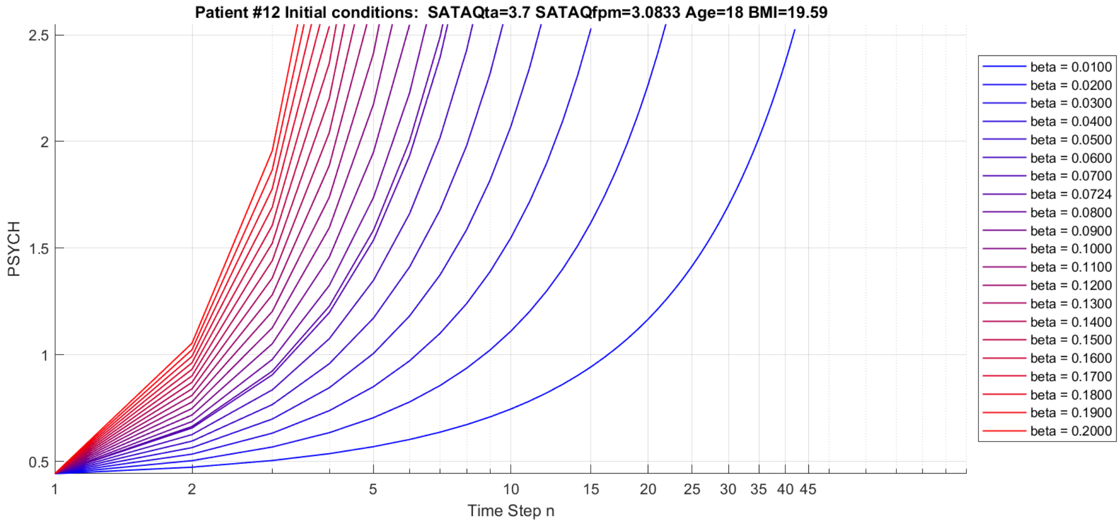
3.2.6 Fitting the dynamic model to real Data

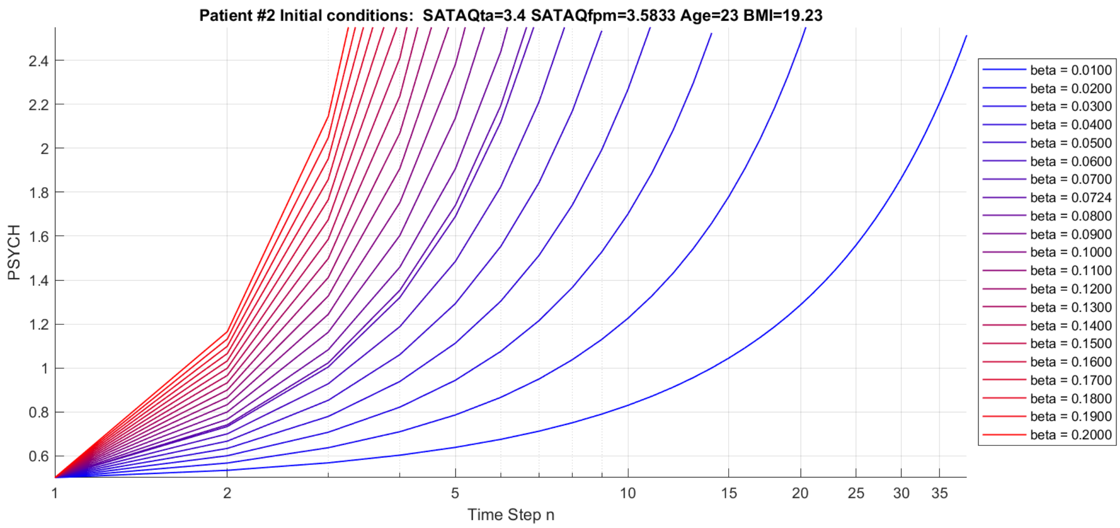
In this last section, the dynamic and discrete mathematical model was applied to the actual data of the patients that were collected.

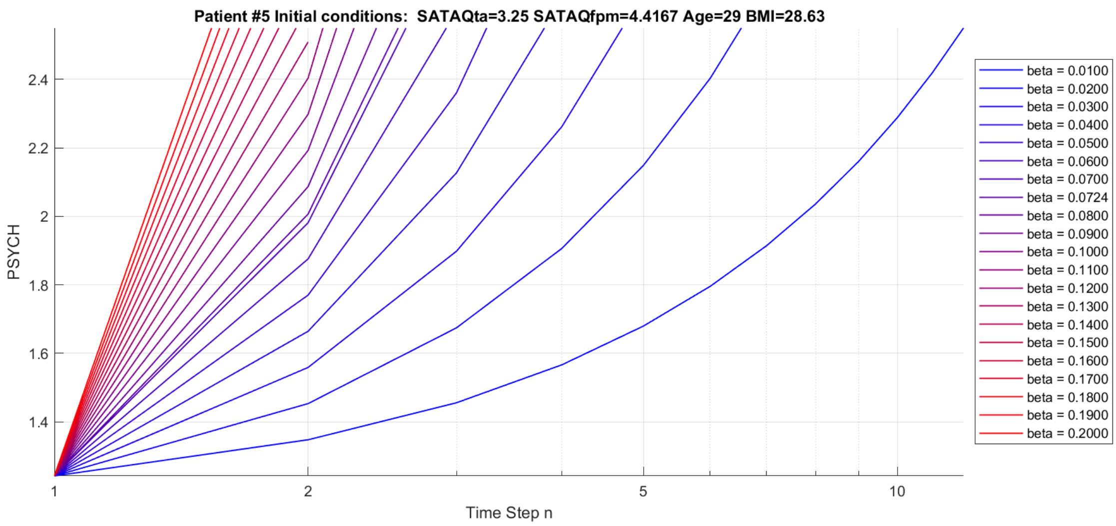
For each patient, the model was applied and a graph was produced showing the trend of PSYCH as beta changed. Actual BMI, SATAQfa, SATAQfpm, and Age were held constant, since only the data from the questionnaires obtained at the time of compilation were available.

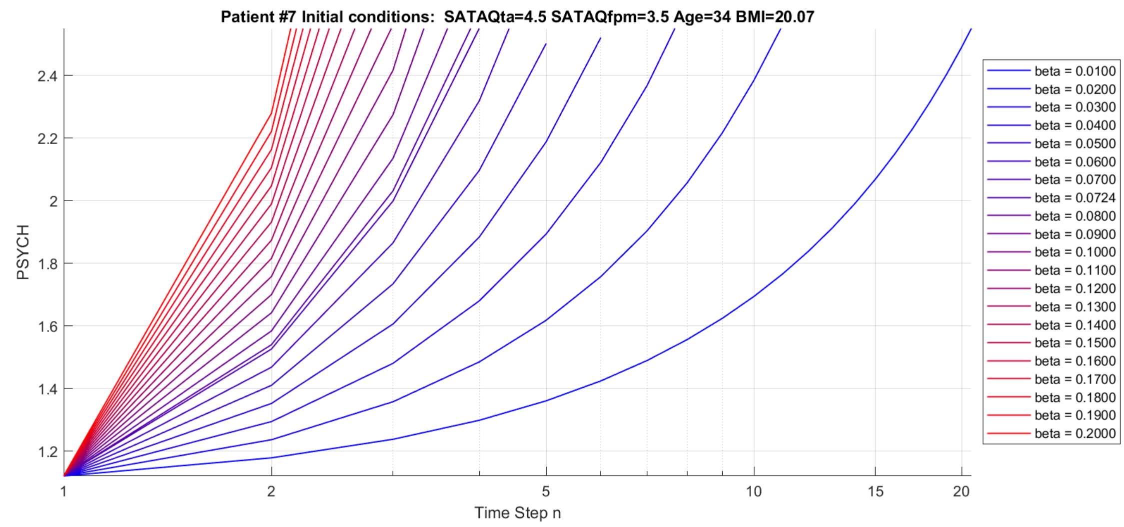
The objective of this part was to observe the influence of beta on the model with different input parameters.

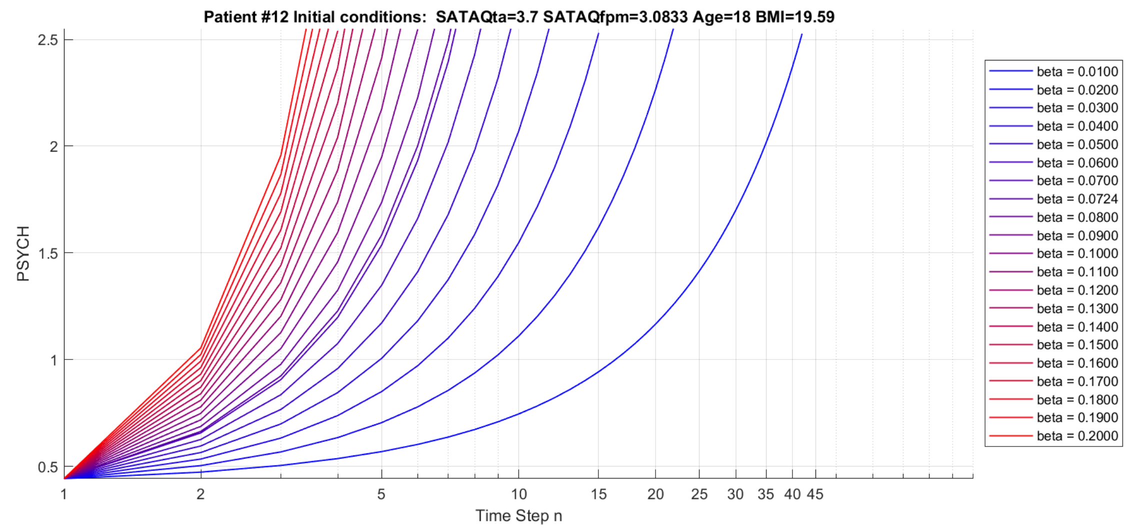
A graph was produced for each of the 279 patients who filled out the questionnaires; for simplicity, only a few are shown in the following images.

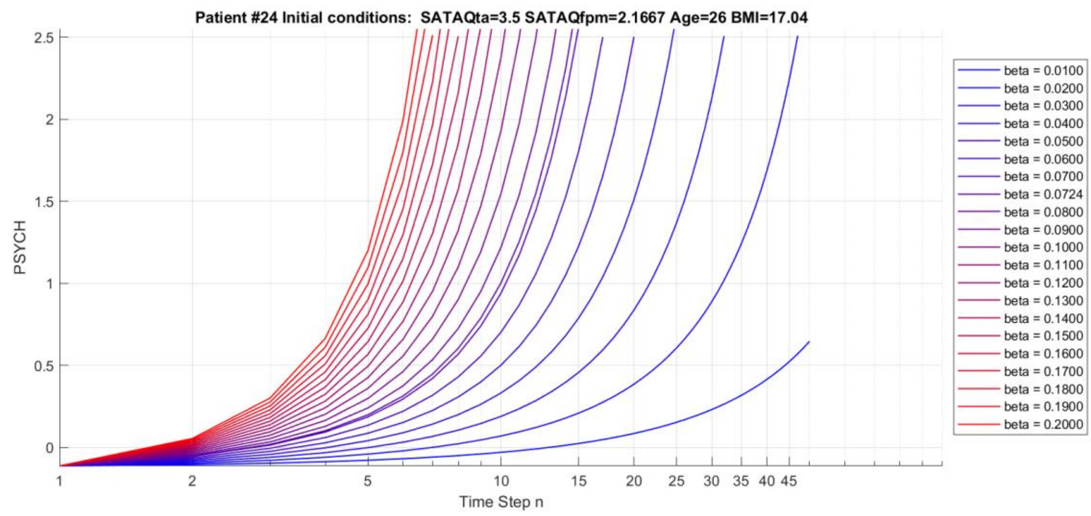

Patient #12 Initial conditions: SATAQta=3.7 SATAQfpm=3.0833 Age=18 BMI=19.59
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000

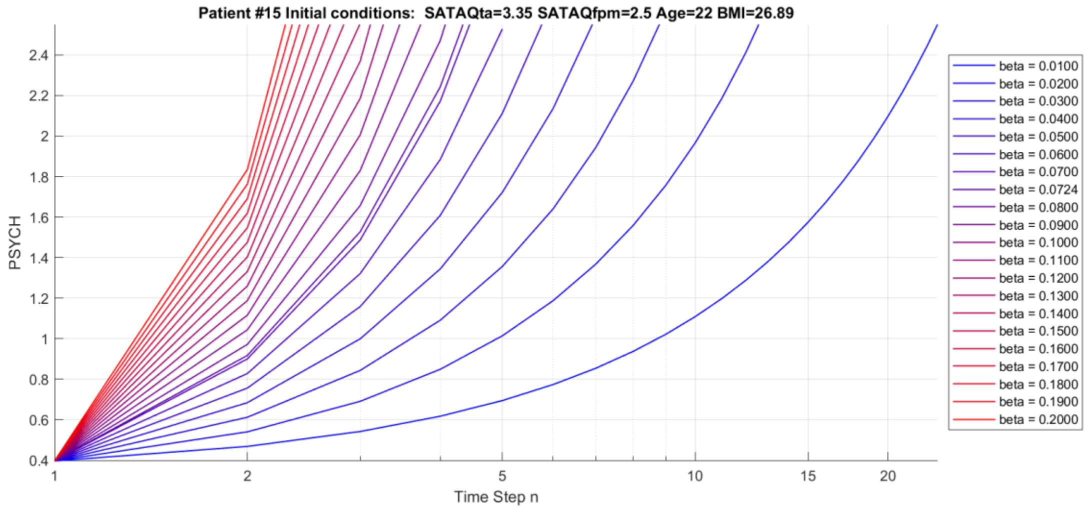

Patient #2 Initial conditions: SATAQta=3.4 SATAQfpm=3.5833 Age=23 BMI=19.23
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000

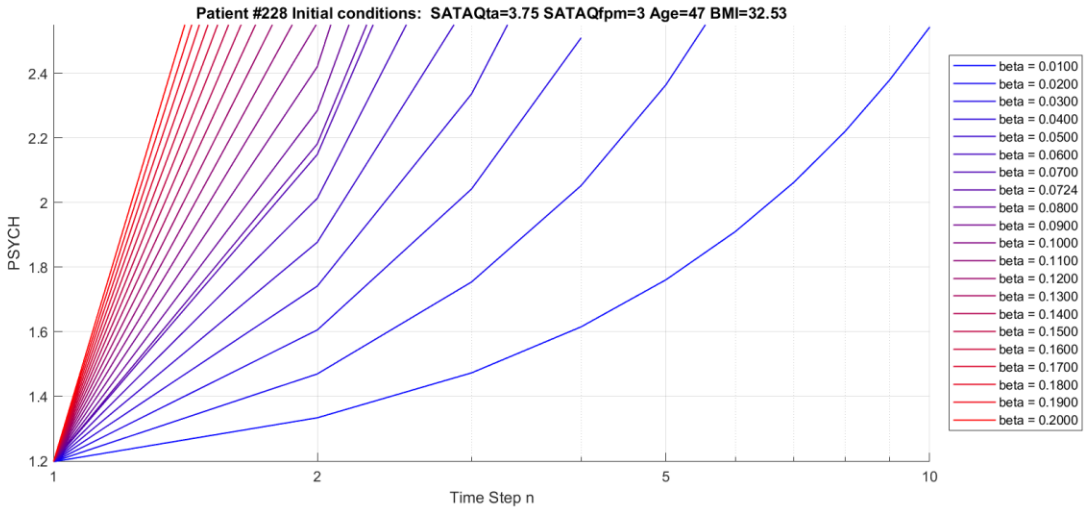

Patient #5 Initial conditions: SATAQta=3.25 SATAQfpm=4.4167 Age=29 BMI=28.63
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000

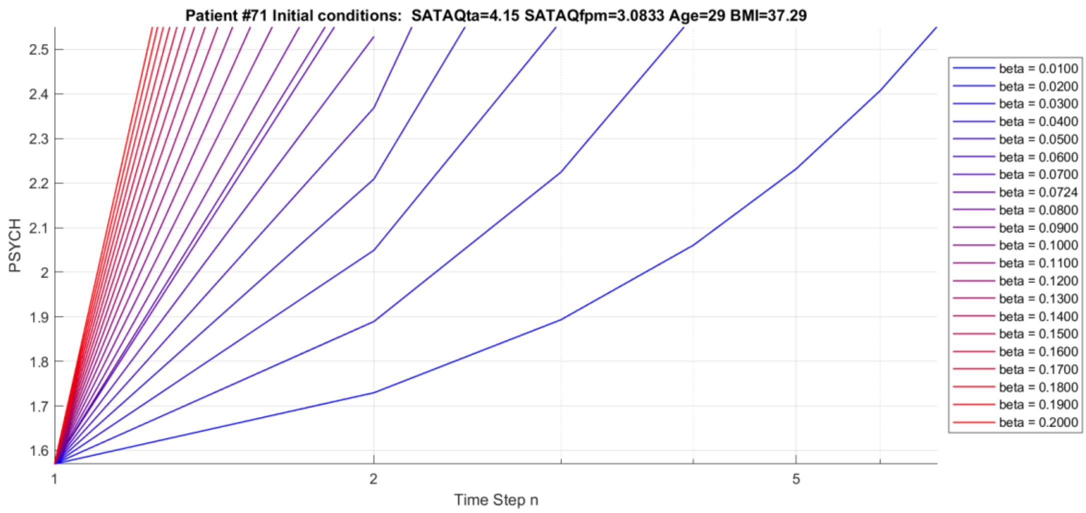

Patient #7 Initial conditions: SATAQta=4.5 SATAQfpm=3.5 Age=34 BMI=20.07
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000


Patient #12 Initial conditions: SATAQta=3.7 SATAQfpm=3.0833 Age=18 BMI=19.59
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000


Patient #24 Initial conditions: SATAQta=3.5 SATAQfpm=2.1667 Age=26 BMI=17.04
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000


Patient #15 Initial conditions: SATAQta=3.35 SATAQfpm=2.5 Age=22 BMI=26.89
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000


Patient #228 Initial conditions: SATAQta=3.75 SATAQfpm=3 Age=47 BMI=32.53
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000


Patient #71 Initial conditions: SATAQta=4.15 SATAQfpm=3.0833 Age=29 BMI=37.29
PSYCH
Time Step n
beta = 0.0100
beta = 0.0200
beta = 0.0300
beta = 0.0400
beta = 0.0500
beta = 0.0600
beta = 0.0700
beta = 0.0724
beta = 0.0800
beta = 0.0900
beta = 0.1000
beta = 0.1100
beta = 0.1200
beta = 0.1300
beta = 0.1400
beta = 0.1500
beta = 0.1600
beta = 0.1700
beta = 0.1800
beta = 0.1900
beta = 0.2000

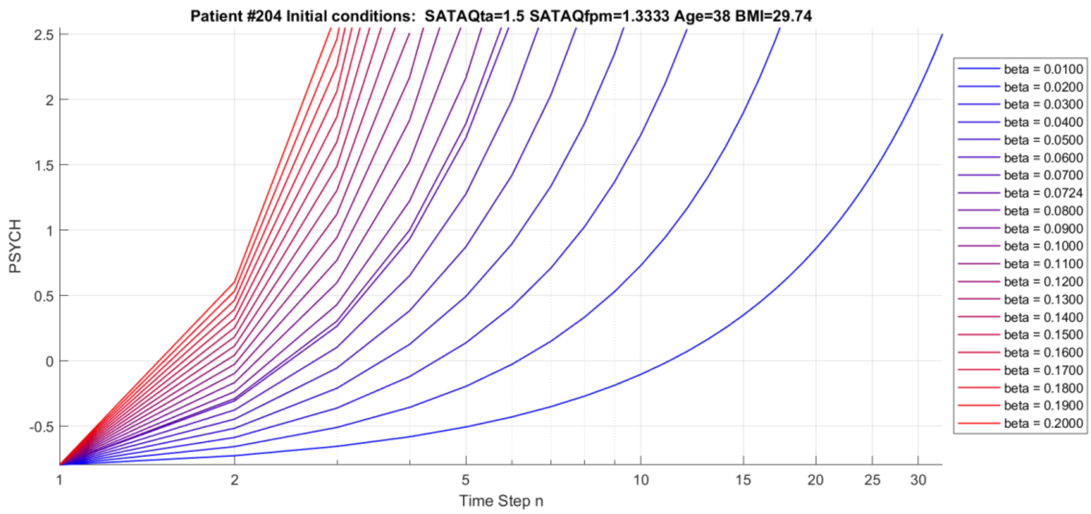


Figure 16: Fitting the dynamic model to real Data

3.3 Discussion of Results for Body Image Project

Summary of results

The purpose of this project was to develop a model that would simulate the evolution of psychological disturbance related to body image, while also taking into account the influence of social pressure, the internalization of an ideal and the actual body mass index.

It started with an initial mathematical model formed by piecing together linear regression equations from the available data. The model was developed in MATLAB-Simulink, and its outputs were analyzed in one, two and three dimensions and showed in corresponding plots.

As desired, as the effective body mass index increased, an increase in psychological disturbance was obtained, as described in the study by Cornelissen at al [14].

However, this model was in continuous time and too simplistic. With the aim of obtaining a dynamic, discreet mathematical model, a new model was derived that considers discrete time steps for all input and output variables.

Finally, this model was applied to individual patient data, looking at different PSYCH graphs as beta varied.

Limitations

The dataset from which the work started is limited in size, a larger one would be more useful for the purposes of the research. Furthermore, the data within it belongs to patients with heterogeneous characteristics. This can be an advantage in some respects, but, for example, limiting the research to patients of the same age could lead to more consistent results.

Finally, it should be emphasized that the data collected refers to a single initial state. Collecting data from patients at multiple time points could lead to the development of more precise dynamic mathematical models over time.

Improvements for future work

The developed discrete-time dynamic model is an initial approach to simulate the effect of body image on mental health. However, the collection of patient data over time is deferred to future work to test its accuracy.

It is also important noting that beta and the minimum time-step beyond which to update model variables are two interrelated unknowns to be discovered in upcoming research.

4. Conclusions

In this thesis work, the aim was to explore the use of AI and mathematical modeling techniques applied to the context of mental health. To this end, two studies with two different research topics were analyzed.

In the first study, psychiatric disorders were analyzed in relation to the presence or absence of PSVT. In this case, AI was developed both to find classification models capable of predicting the disease and to establish psychological risks factors for PSVT. Our results showed the importance of MHLC and MMPI-2 scales and a good performance of models such as Support vector machine and Quadratic Discriminant Analysis. Experiments with other machine learning models and unproven statistical techniques on the PSVT study are postponed for future purposes.

In the second study, we investigated the development of a mathematical model capable of simulating the evolution of psychological disorders over time based on body image. From an initial continuous-time model, a new discrete-time model was created. This result is intended as a starting point to investigate the development of predictive mathematical models for body image and its relationship with mental health and eating disorders. We invite to improve the found discrete mathematical model, investigating a function able to represent beta in an optimal way and the determination of the minimum time step.

However, as demonstrated by the results obtained in this thesis, AI and mathematical modeling algorithms have been proven to be valuable tools in the field of mental health research. In addition, new datasets or expanding existing ones would help to achieve even better results.

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