MEASURING EFFORTFUL MOTIVATION WITH HEFFORT: PSYCHOMETRIC TESTING AND VALIDATION USING MACHINE LEARNING

by

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ACADEMIC ETHICS AND INTEGRITY STATEMENT

I, Alamira Jouman Hajjar, hereby certify that I am aware of the Academic Ethics and Integrity Policy issued by the Council of Higher Education (YÖK) and I fully acknowledge all the consequences due to its violation by plagiarism or any other way.

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ABSTRACT

MEASURING EFFORTFUL MOTIVATION WITH HEFFORT: PSYCHOMETRIC TESTING AND VALIDATION USING MACHINE LEARNING

Lack of motivation can affect everyone in our modern world, with consequences ranging from poor work and school performance to decreased family functioning. Thus, it is important to understand the mechanisms of motivation and devise personalized treatments. Traditionally, motivational and other psychological states in humans are measured with questionnaires. However, none of the current questionnaires can distinguish between motivation and pleasure, two components of the reward system. This is in contrast to how the brain works which employs the dopamine system to mediate effortful motivation and the opiate system to mediate pleasure. Importantly, deficits in either system require a different treatment and thus it is pertinent that we can distinguish between these psychological states. To address this issue, our group has developed a novel questionnaire (HEFFORT) that we administered to a representative sample of Istanbulites varying in age, income, and lifestyle. We tested the hypothesis that HEFFORT can separate motivation from pleasure. First, we explored the relationships between the novel and validated questionnaires using Spearman correlations. Second, we developed an algorithm that predicts individual differences in effortful motivation using supervised machine learning classification techniques. Third, we determined the accuracy of the predictions by testing the algorithm on a separate testing dataset. Our results show that HEFFORT is reliable and able to distinguish between effortful motivation and pleasure. Future testing and use can establish HEFFORT as a research and clinical diagnostic tool that assesses different components of reward.

Keywords: Motivation, Pleasure, Psychometrics, Quality Of Life, Machine Learning, Artificial Intelligence, Decision Trees.

ÖZET

HEFFORT ILE ÇABA GEREKTİREN MOTİVASYONU ÖLÇMEK: MAKİNE ÖĞRENİMİ KULLANARAK PSİKOMETRİK TEST VE DOĞRULAMA

Motivasyon eksikliği modern dünyamızdaki herkesi etkileyebilir. Düşük iş ve okul performansından azalan ailesel ilişkilere kadar değişen farklı sonuçları olabilir. Bu nedenle motivasyon mekanizmalarını anlamak ve kişiselleştirilmiş tedaviler tasarlamak önemlidir. Geleneksel olarak insanlarda motivasyon ve diğer psikolojik durumlar anketlerle ölçülür. Ancak, mevcut anketlerin hiçbiri ödül sisteminin iki bileşeni olan motivasyon ve haz arasında ayrım yapamaz. Bu ise beynin çalışma ilkelerine aykırıdır; beyin motivasyona aracılık etmek için dopamin sistemini, haz için ise opiyat sistemini kullanır. Daha da önemlisi, her iki sistemdeki eksiklikler farklı bir tedavi gerektirir ve bu nedenle ilgili psikolojik durumların ayırt edilmesi gerekmektedir. Bu sorunu çözmek için geliştirilen yeni bir anket (HEFFORT), yaş, gelir ve yaşam tarzı açısından farklı İstanbulluların temsili bir örneğine bu tez çerçevesinde uygulandı. HEFFORT'un motivasyonu hazdan ayırabileceği hipotezi test edilmiştir. İlk olarak, yeni ve doğrulanmış anketler arasındaki ilişkiler Spearman korelasyonlarını kullanılarak araştırıldı. Daha sonra, denetimli makine öğrenimi olan sınıflandırma teknikleri kullanılarak çaba gerektiren motivasyondaki bireysel farklılıkları tahmin eden bir algoritma geliştirildi. Son olarak, algoritmayı ayrı bir test veri setinde inceleyerek tahminlerin doğruluğu belirlendi. Sonuçlarımız HEFFORT'un güvenilir olduğunu ve çaba gerektiren motivasyon ile haz arasında ayrım yapabildiğini göstermektedir. Böylelikle HEFFORT ödül sistemin farklı bileşenlerini değerlendiren gelecek araştırmalarda ve klinik teşhis aracı olarak kullanılabilir.

Anahtar Sözcükler: Motivasyon, Haz, Psikometri, Yaşam kalitesi, Makine öğrenimi, Yapay zeka, Karar ağaçları.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

a	Pleasure items in HEFFORT
b	Pleasure and Effort compound items in HEFFORT
b/a	effortful motivation items in HEFFORT

LIST OF ABBREVIATIONS

BDI	Beck's Depression Inventory
DARS	Dimensional Anhedonia Rating Scale
MEI	Motivation and Energy Inventory
SHAPS	Snaith-Hamilton Pleasure Scale
ML	Machine Learning
MLR	Multiple Linear Regression
NAc	Nucleus Accumbens
VP	Ventral Pallidum
VTA	Ventral Tegmental Area
PFC	Prefrontal Cortex
SNc	Substantia Nigra pars compacta
STR	Striatum
H-Sc	Hygiene and Self-care item
F	Food (smell/taste) item
FG	Easy/Feel-good item
S-Sc	Social/Self-care item
M	Mental item
N	Novelty/Surprise item
Ph	Physical activity item
Soc	Social Activity item
S-Ph	Social-Physical item

1. INTRODUCTION

Motivation allows individuals to complete everyday tasks, like getting up to work, raising a child, running a company, or overcoming an illness. In the same way, lack of motivation has consequences ranging from losing a job, failing at study, neglecting physical health, to exacerbating mental health issues. Therefore, measuring motivation, and the lack of it, is important for research and clinical assessment, and developing recommendations for a healthy lifestyle and a productive society.

To understand individual differences in motivational behavior, questionnaires have been designed and used for a long time. Such questionnaires tend to assess multiple motivational constructs at the same time. Questions such as "I enjoy doing this activity" or "this activity makes me happy" [1] assess both the pleasure of doing an activity and the effort one puts in doing it.

On the other hand, research in neuroscience shows that the pleasure and effort-related motivation systems are located in different brain regions and mediated by different receptors and neurotransmitters [2]. The hedonic circuit, typically controlling the pleasure or "liking" experience in humans and animals, is mediated by the opioid system in the prefrontal and orbitofrontal cortices, insula, anterior cingulate, nucleus accumbens (NAc), ventral pallidum (VP), and amygdala. Stimulating these hotspots is necessary in enhancing "liking" reactions via an interaction between their anatomical site and their current neurochemical state or mode of stimulation [3].
By contrast, effort-related motivation is mediated by the dopamine system. Dopaminergic (DA) neurons project from the Ventral Tegmental Area (VTA) to the NAc in what is called the mesolimbic pathway. DA neurons project also from the VTA to the prefrontal cortex (PFC) in the mesocortical pathway, as well as from the Substantia Nigra pars compacta (SNc) to the striatum (STR), but the later pathway is more related to movement tuning than to motivation. DA pathways are activated by reward-related stimuli but do not cause sensory pleasure. For example, a study on a

psychiatric patient showed that stimulating the mesolimbic pathway using electrodes did not cause the patient to feel the pleasure of sex, but to feel motivated to engage in sexual activity [4]. You can observe the circuits in Figure [1].

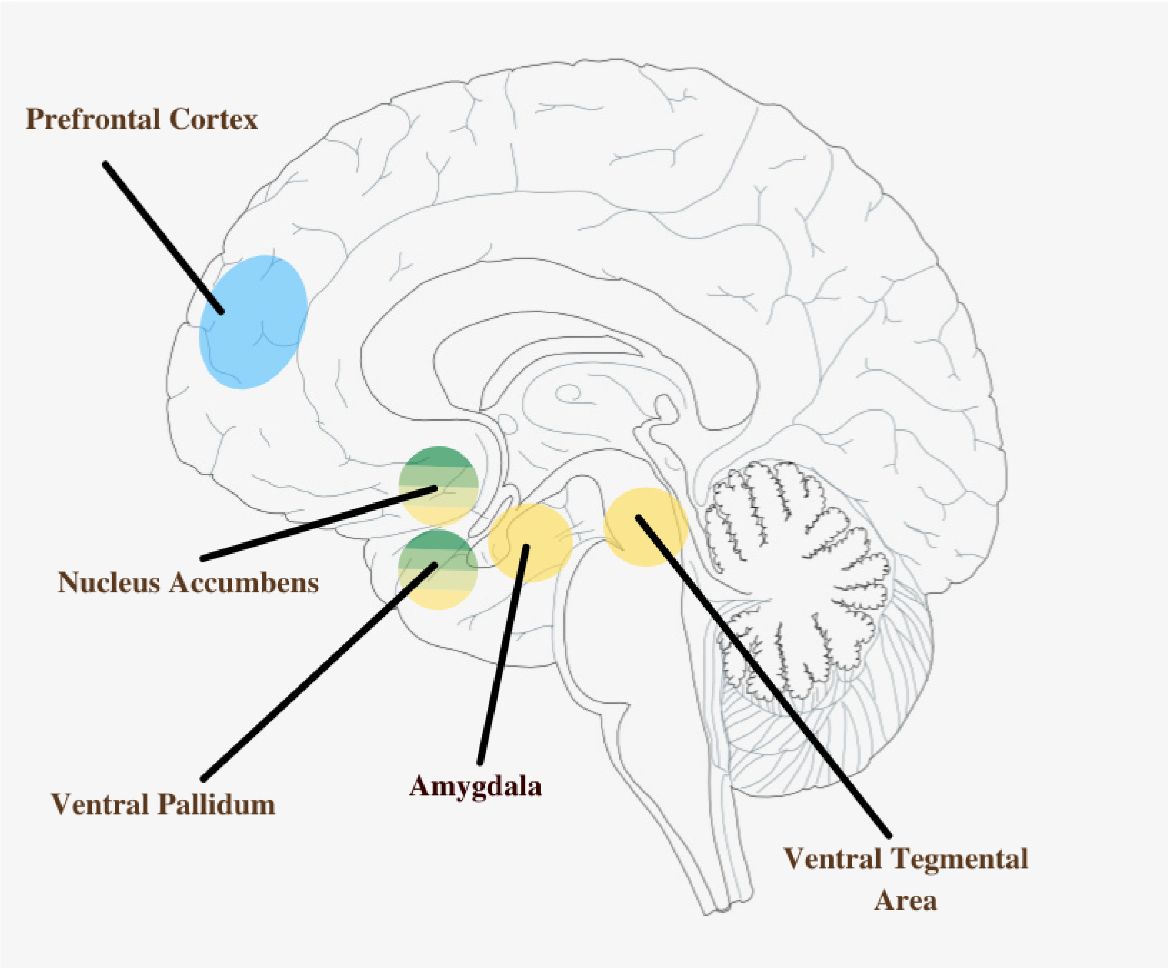

Figure 1.1 brain substrates of different components of reward. Brain regions linked to "liking" (green), "wanting" (yellow), and cognitive incentive processing (blue). Color-coding adapted from "Parsing Reward", by Kent C. Berridge and Terry E. Robinson.

1.1 Brain circuits' independence

Evidence for the independence of the opioid and dopamine circuits comes from studies revealing that the destruction of one circuit does not evidently mean the destruction of the other. For example, following extensive destruction of dopamine neurons to approximately 1% normal levels using the neurotoxin 6-hydroxydopamine, orofacial "liking" reactions to sweetness remained intact [5]. Moreover, patients with Parkinson"s Disease, who suffer from dopamine depletion due to the degeneration of neurons in the SN, were not impaired in ratings of how much they "liked" the taste of something sweet [6].

However, despite the separation of the pleasure and effort-related motivation systems in the brain, these constructs are typically treated as one in clinical diagnostic systems and research tools like questionnaires. For example, the loss of interest or pleasure in a previously rewarding activity is defined as a core symptom of depression in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), and questionnaires such as Beck's Depression Inventory (BDI) [7] which measure 'depression'. BDI's utility has been examined for measuring depression in medical setting and was found to be acceptable to patients and clinicians, covers DSM-3 diagnostic criteria for major depressive disorder, and shows good correlation with measures of depression and anxiety, as well as high reliability as an indicator of symptom severity and suicidal thoughts [8]. Difference between scores on the Beck Depression Inventory in healthy controls and MDD patients is reported in Table 1.1.

Table 1.1
Difference between scores on the Beck Depression Inventory in healthy controls and MDD patients, Cited from Turner et al,. 1984.

		Depressed (N=12)	Nondepressed (N=28)	p
BDI	Mean	20.25	8.64	<0.001
	SD	7.38	5.42	

Other examples include the Motivation and Energy Inventory (MEI) [9], which measures energy, fatigue and social motivation. The psychometric results of two randomized, placebo-controlled clinical trials confirmed that this questionnaire is internally consistent, and is responsive to the three MEI subscales [9]. Internal consistency (standardized Cronbach's a coefficients) for the MEI subscale scores at baseline for both trials are reported in Table 1.2.

Table 1.2
Internal consistency (standardized Cronbach's a coefficients) for the MEI subscale scores at baseline for two trials. Cited from Fehnel, 2004.

	Study 1	Study 2
Mental Energy	0.87	0.89
Social Motivation	0.82	0.84
Physical Energy	0.75	0.76

One other example is the Dimensional Anhedonia Rating Scale (DARS) [1], which measures desire, pleasure, effort and motivation. A study involving 102 patients and healthy controls demonstrated that DARS is reliable in identifying major depressive disorder (MDD) as well as linked to dopamine receptor binding in humans, both of which have predictive potential for treatment outcome [1]. Difference in DARS score between MDD and Healthy Controls in pivotal validation trial is reported in Figure 1.2.

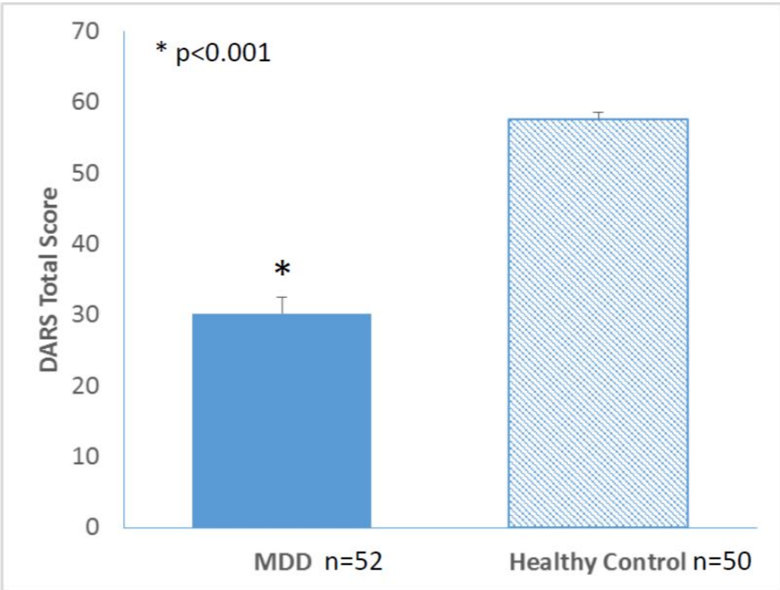

Figure 1.2 Difference in DARS score between MDD and Healthy Controls in pivotal validation trial. Cited from Rizvi, 2015.

However, none of these tools assess effort-related motivation separately from pleasure, although pleasure is sometimes measured on its own. For example, the Snaith-Hamilton Pleasure Scale (SHAPS) [10] asks questions such as "I would feel pleasure

when I receive praise from others".
A study on 461 adult outpatients with MDD examined the psychometric properties of SHAPS and confirmed that this questionnaire has excellent consistency, with construct validity, and is unidimensional in assessing hedonic capacity among the adult outpatients with MDD. The study also showed that SHAPS is not influenced by participant's demographic and clinical characteristics [11]. Another study on 362 participants indicated that SHAPS measures two components of anhedonia, social and physical [12]. Factorial structures of SHAPS are reported in Table 1.3.

1.2 The need for a motivation scale

This lack of separation is problematic because patients may be impaired in a function of one construct but not the other, and thus need tools that can separately assess these constructs, and consequently, therapeutics which target only one system. In many cases, physicians may prescribe antidepressant medication for patients complaining of depressive mood, regardless of whether the symptoms suggest a clear responsiveness to specific receptor-targeting antidepressants [13].

To address this issue, our group has previously developed a novel questionnaire, termed the hedonia and effort scale (HEFFORT scale), which aims to separate effort-related motivation from pleasure. The questionnaire consists of 33 items, all items are of 2 parts. The (a) part measures pleasure, and the (b) part measures a combination of pleasure and effort typically assessed in standard questionnaires. We hypothesize that effort can be extracted by computing the ratio of b/a. In the present study, I will determine whether the b/a ratio can distinguish between pleasure and effort-related motivation. If validity of the HEFFORT scale can be established, it will have a great impact as a research and clinical diagnostic tool to help with more accurate diagnoses and targeted therapies.

Table 1.3

Factorial structures of SHAPS. Cited from original study by Langvik et al., 2019.

	Social anhedonia	**Physical anhedonia**
alpha	0.87	0.81
I would be able to enjoy a beautiful lanscape or view	0.86	
I would get pleasure from helping others	0.79	
I would enjoy seeing other people smiling	0.78	
I would find pleasure in small things; e.g. bright sunndy day	0.71	
I would find pleasure in the scent of flowers or the smell of a fresh sea breeze	0.59	
I would feel pleasure when I receive praise from other people	0.58	
I would enjoy looking smart when I have made an effort with my appearance	0.44	
I would enjoy my favorite TV or radio program		0.83
I would find pleasure in my hobbies and pastimes		0.63
I would enjoy being with family or close friends		0.6
I would enjoy reading a book, magazine or newspaper		0.55
I would be able to enjoy my favorite meal		0.54
I would enjoy a warm bath or refreshing shower	0.35	0.46
I would enjoy a cup of tea or coffee or my favorite drink	0.42	0.43

1.3 Novelty

It has been established that effort-related motivation and pleasure are mediated by different substrates in the brain [6],[5]. Thus, it is necessary to change the way clinical diagnosis questionnaires treat them both as one. Leading to improvement of the accuracy of diagnosis and therapeutic interventions. Therefore, the novel HEFFORT questionnaire developed by D. Schulz is intended to fill a critical void in motivation-assessment diagnosis.

The team has previously collected data from 272 volunteers who filled out their information, and answered the questionnaires' items, including Dimensional Anhedonia Rating Scale (DARS) measuring desire, motivation, effort, and pleasure across reward domains [1], Motivation and Energy Inventory (MEI) assessing mental energy, physical energy, and social motivation [9], Snaith-Hamilton Pleasure Scale (SHAPS) measuring hedonic experience, quality of life and satisfaction, social interaction, and sensory experience [10], Beck Depression Inventory (BDI-IA) measuring self-reported depression [7], and the new HEFFORT questionnaire. In addition to standard reliability tests and Spearman correlation analyses, our study has benefited from novel artificial intelligence (AI) techniques in different aspects. We have applied decision tree algorithms to extract the characteristics of individuals with high and low motivation, determined the accuracy of the new questionnaire in predicting motivation levels, and, by using cross-validation, split the data and test the questionnaire's accuracy on a specific dataset.

1.4 Machine Learning: K-Means Clustering and Decision Trees

Machine learning (ML) is a branch of artificial intelligence (AI) that focuses on building predictive models such that they learn from data to increase accuracy without being programmed to do so.

In ML, the algorithm is trained to find patterns and features in the data to make

decisions and predictions about test data or new data.
The type of ML algorithm depends on the type of data one is using to train the model on, whether it is labeled -identifies certain characteristics- or unlabeled. Algorithms used with labeled data include regression, instance-based algorithms, and decision trees. For unlabeled data, clustering, association algorithms, and neural networks are used. In this study we used both unsupervised k-means clustering algorithm, and supervised decision trees (DT) algorithm.

1.4.1 K-Means Clustering

K-means clustering is an unsupervised machine learning algorithm that collects data points and aggregates them together because they share certain similarities, thus, forming a cluster. The similarity of two points in a cluster is determined by the distance between them.
Clustering is used to partition the data into (k) number of clusters by finding structures in unlabeled dataset.
The most common method to measure distance between two points is the Euclidean Distance, minkowski distance with p=2, which is calculated by using the square of the difference between x and y coordinates of the points in a 2-dimensional space.
K-means algorithm cannot determine the number of clusters; therefore, the user defines (k) based on the wanted outcome.
Additionally, k-means is an iterative algorithm. After the (k) number of clusters is determined, the algorithm performs the following steps:

1. Select random centers of cluster (centroids) for each cluster.
2. Calculate the distance of each point in the dataset to the centroids.
3. Assign points to the closest cluster.
4. Iterate the process to find new centroids based on the means of the data points in the cluster until all points converge and cluster centers stop moving.

An example of data clustering is shown in Figure 1.3.

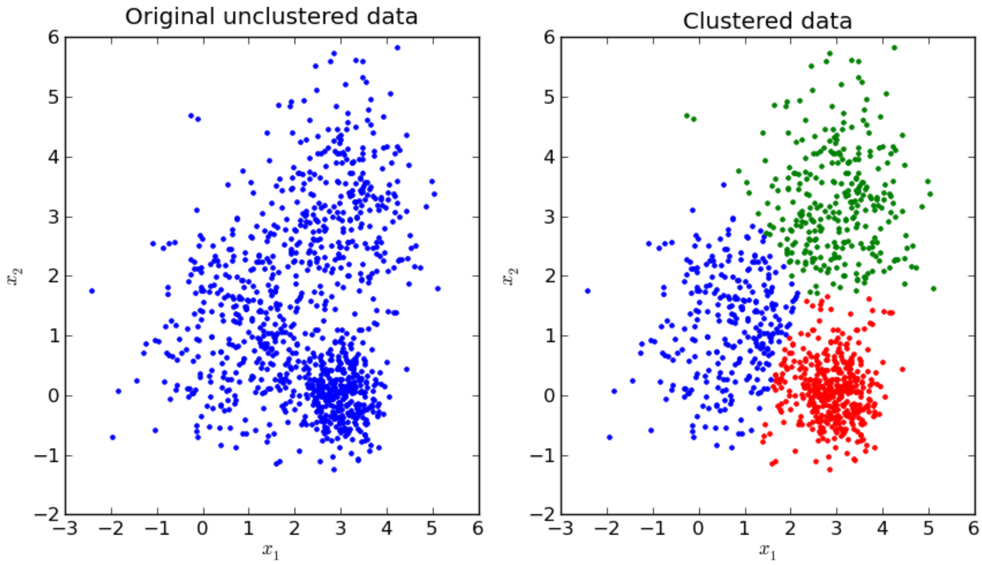

Figure 1.3 Before and after applying k-means clustering on unlabeled dataset.

1.4.2 Decision Trees

Decision Trees are a non-parametric supervised learning method used for both classification and regression tasks. A DT algorithm creates a model that predicts the value of a target (dependent) variable based on several input (independent) variables. A tree is built by splitting the source set, constituting the root node of the tree, into subsets constituting the successor children. The splitting is based on a set of splitting rules based on classification features.

Decision trees can be used for segmentation, stratification, interaction identification, data reduction, and predictions. The dependent and independent variables can be nominal, ordinal, or continuous.

As for tree growing methods, they can be:

CHAID: Chi-squared Automatic Interaction Detection. At each step, CHAID chooses the independent (predictor) variable that has the strongest interaction with the dependent variable. Categories of each predictor are merged if they are not significantly different with respect to the dependent variable.

Exhaustive CHAID: A modification of CHAID that examines all possible splits for each predictor.

CRT: Classification and Regression Trees. CRT splits the data into segments that are as homogeneous as possible with respect to the dependent variable. A terminal node in which all cases have the same value for the dependent variable is a homogeneous or pure node.

QUEST: Quick, Unbiased, Efficient Statistical Tree. A method that is fast and avoids other methods' bias in favor of predictors with many categories. QUEST can be specified only if the dependent variable is nominal.

Decision Tree Diagram Explanation

For example, we want to predict age of participants based on their demographics, place, gender, education, income, psychiatric medicine. Using CHAID DT algorithm, we enter the age variable as our dependent target and other variables as independent inputs. The output is a tree-like diagram with the predicted variable (age) as primary node, and predictors (education, gender) in the branches. Figure 1.4.

In the primary node we observe that the average predicted age is 33. We then observe that the most significant predictor of age is education, with people who have earned degrees less or equal to a college (yüksekokul) education are of older age (predicted age = 41), while those with higher degrees are younger (predicted age = 30).

Participants who have pursued higher education were best predicted by gender. Males who pursued university are older (predicted age = 33) than women who did so (predicted age = 27).

Therefore, we understand that education, followed by gender, are predictors of age in our sample. On the other hand, place, income, and psychiatric medicine use do not influence the algorithm's decision when predicting the age variable.

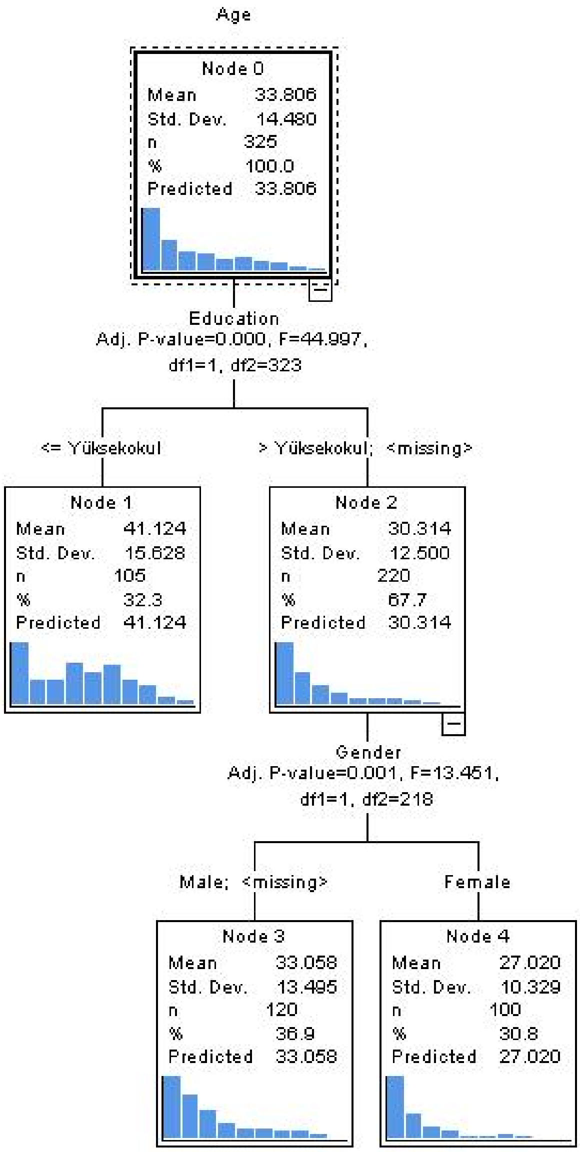

Figure 1.4 Decision tree diagram for predicting age based on demographics.

Decision Tree Validation

Validation allows the user to assess the algorithm's ability to generalize to a larger population. Thus, avoiding overfitting, or an analysis that only predicts correct responses to a particular set of data.

There are two methods of validation: Cross-validation and Split-Sample validation.

Cross-validation divides the dataset into subsets (folds) such that generated tree models exclude fold data. For example, the first tree model is based on all cases except those in the first fold, the second tree excludes cases in second fold, and so on.

Split-sample validation divides the dataset into training and test sets. To enhance the generated model accuracy, we can add a validation set. Thus, we can evaluate the performance of the trained model on the validation set, choose the model with the best validation set performance, and then evaluate the performance on the test set. Figure 1.5.

Common ratios are:
70% train, 15% validation, 15% test.
80% train, 10% validation, 10% test.
60% train, 20% validation, 20% test.

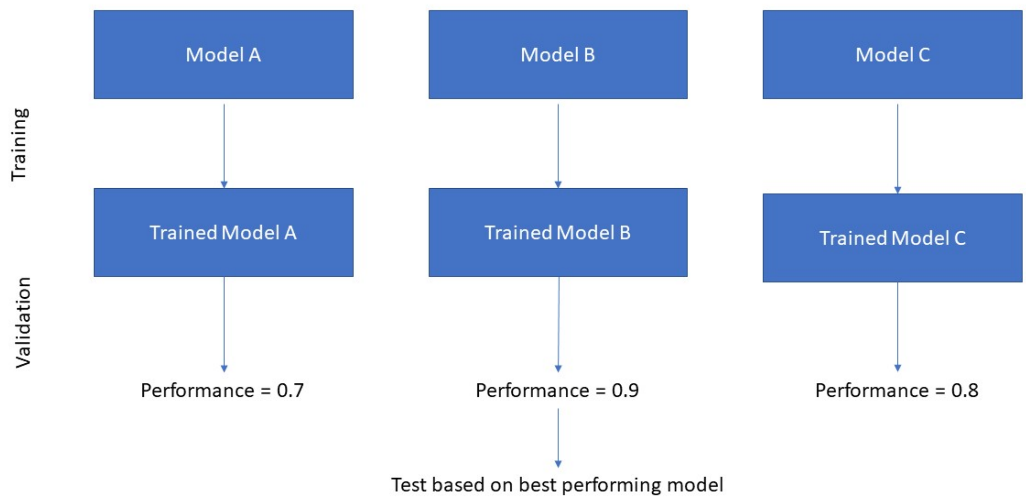

Figure 1.5 Split-sample using validation set diagram. Adapted from Machine Learning and Medicine, Rachel Draelos, 2019.

2. MATERIALS AND METHODS

2.1 Participants

Written informed consent was obtained before the participants filled out any forms. The Ethics Committee of Yeditepe University approved all study procedures, and the study was conducted in accordance with the Declaration of Helsinki
The data of this study were collected between November 2017 and August 2018 under the direction of D. Schulz (faculty at Yeditepe University at that time). Participants in this study were recruited randomly from the population of Istanbul city from the streets in 6 different areas of the city:
1.Karaköy
2.Kadiköy
3.Beyoğlu
4.Beşiktaş
5.Uskudar
6.Bostanci
Exactly 330 adults filled out their information (age, gender, education, salary group, use of psychiatric drugs), and answered Turkish-translations of previously validated questionnaires including DARS, MEI, SHAPS, and BDI-IA, as well as, the novel HEF-FORT questionnaire.
Age groups were separated into 6 groups:
1) 18-25, 2) 26-33, 3) 34-41, 4) 42-49, 5) 50-57, 6) 58-65+.
Income groups were divided into 5 groups:
1) 0-1500
2) 1501-2500
3) 2501-4000
4) 4001-8000
5) 8001+.
No type of reward was given to the volunteers in return of their participation in our

study.

Personal identifiers (e.g. names, birthdates, social security numbers) were not collected, allowing anonymity.

2.2 Questionnaires

In the current study we used 4 different validated questionnaires to measure self-reported depression, hedonic experience, motivation, effort, and fatigue. And the novel HEFFORT questionnaire as a new measurement of effort-related motivation.

2.2.1 HEFFORT

Developed by D. Schulz, in the interest of measuring pleasure separately from the willingness to expend effort on a task that one finds pleasurable. It consists of 33 items, scaled from 1-6, each item has two parts, the (a) part scales pleasure, for example (I like fit body types, I love parties, food, people.), whereas the (b) part scales the activity necessary to obtain a pleasurable goal. As such, the (b) scale represents a compound (effort + pleasure) put into performing the activity to obtain pleasure as scaled in part (a). For example, (I work out to have a fit body type, I love to host parties, to make food, to meet new people.). Items are reported in Table 2.1.

Table 2.1
HEFFORT items. Note that 1 signifies totally disagreeing and 6 signifies absolutely agreeing.

1a)	I love the taste of sweets	1	2	3	4	5	6
1b)	I would walk miles to buy sweets	1	2	3	4	5	6
2a)	I love tasting new foods	1	2	3	4	5	6
2b)	I make new foods	1	2	3	4	5	6
3a)	I love animals	1	2	3	4	5	6
3b)	I (would) take care of animals	1	2	3	4	5	6
4a)	I love plants	1	2	3	4	5	6
4b)	I (would) love gardening	1	2	3	4	5	6
5a)	I love kids	1	2	3	4	5	6
5b)	I love playing with kids	1	2	3	4	5	6
6a)	I love to be surrounded by friends	1	2	3	4	5	6
6b)	I make time to meet with friends	1	2	3	4	5	6
7a)	I love the seaside	1	2	3	4	5	6
7b)	I (would) make time to be by the seaside	1	2	3	4	5	6
8a)	I like hygiene	1	2	3	4	5	6
8b)	I spend time on personal hygiene	1	2	3	4	5	6
9a)	I love to spend money	1	2	3	4	5	6
9b)	I would work harder to have more spending money	1	2	3	4	5	6
10a)	I like fit body types	1	2	3	4	5	6
10b)	I work out to have a fit body type	1	2	3	4	5	6
11a)	I love my home	1	2	3	4	5	6
11b)	I love entertaining/socializing in my home	1	2	3	4	5	6
12a)	I love people	1	2	3	4	5	6
12b)	I love to discuss topics with people	1	2	3	4	5	6
13a)	I love parties	1	2	3	4	5	6
13b)	I love to give parties	1	2	3	4	5	6

14a)	I love nature	1	2	3	4	5	6
14b)	I love walking/hiking in nature	1	2	3	4	5	6
15a)	I love dogs	1	2	3	4	5	6
15b)	I love to train dogs	1	2	3	4	5	6
16a)	I love food	1	2	3	4	5	6
16b)	I love cooking	1	2	3	4	5	6
17a)	I love my home	1	2	3	4	5	6
17b)	I love cleaning my home	1	2	3	4	5	6
18a)	I love music	1	2	3	4	5	6
18b)	I love discovering music	1	2	3	4	5	6
19a)	I like people	1	2	3	4	5	6
19b)	I like meeting new people	1	2	3	4	5	6
20a)	I love my friends	1	2	3	4	5	6
20b)	I love doing things for my friends	1	2	3	4	5	6
21a)	I love art	1	2	3	4	5	6
21b)	I make art	1	2	3	4	5	6
22a)	I love good food	1	2	3	4	5	6
22b)	I would take cooking classes	1	2	3	4	5	6
23a)	I love fruits	1	2	3	4	5	6
23b)	I prepare fruit salads/smoothies	1	2	3	4	5	6
24a)	I love bread	1	2	3	4	5	6
24b)	I (would) make bread myself	1	2	3	4	5	6
25a)	I love home cooked food	1	2	3	4	5	6
25b)	I make home cooked food	1	2	3	4	5	6
26a)	I love the sun	1	2	3	4	5	6
26b)	I love spending time under the sun	1	2	3	4	5	6
27a)	I love to see the sunrise	1	2	3	4	5	6
27b)	I love to wake up early to watch the sunrise	1	2	3	4	5	6

28a)	I love swimming pools	1	2	3	4	5	6
28b)	I love to swim in pools	1	2	3	4	5	6
29a)	I love sports	1	2	3	4	5	6
29b)	I love doing sports	1	2	3	4	5	6
30a)	I love books	1	2	3	4	5	6
30b)	I love reading books	1	2	3	4	5	6
31a)	I love to see people smile	1	2	3	4	5	6
31b)	I make people smile	1	2	3	4	5	6
32a)	I love chocolate	1	2	3	4	5	6
32b)	I would walk miles to buy chocolate	1	2	3	4	5	6
33a)	I love new outfits	1	2	3	4	5	6
33b)	I love to shop for new outfits	1	2	3	4	5	6

2.2.2 BDI-IA

Beck Depression Inventory BDI-IA is a revised version of BDI, a widely used inventory to define severity of depression. It contains 21 items, scaled from 0-3, that positively correlate with self-reported depression [14]. The maximum score than can be obtained in this test is 63, implying severe depression. According to American population, a classification of the cut-off scores of minimal, mild, moderate, and severe depression is 0-9, 10-18, 19-29, and 30-63, respectively.

The questions measure different states such as sadness, guilt, insomnia, social withdrawal, and body image changes. For example:

Q12).

0 I have not lost interest in other people.

1 I am less interested in other people than I used to be.

2 I have lost most of my interest in other people.

3 I have lost all of my interest in other people.

2.2.3 DARS

Dimensional Anhedonia Rating Scale is a validated questionnaire used to measure desire, motivation, effort, and pleasure across reward domains [1]. It consists of

20 items, 4 subscales (A hobbies and pastimes, B foods and drinks, C social activities, and D sensory experiences) each having 4 items scaled from 1-5, with a maximum score of 100.

The items were designed to separate the pleasure factor from effortful behavior, but do not clearly achieve that in all scales. For example, items A1, I enjoy doing this activity, A3, I want to do this activity, C11, this activity always makes me happy, these items correlate highly with pleasure but also with effort to perform the activity itself.

A low score on DARS implies lack of pleasure and motivation. The English version was translated into Turkish by the present authors.

2.2.4 MEI

Motivation and Energy Inventory [9] originally consists of 30 items categorized into 3 subscales assessing mental energy, physical energy, and social motivation. Items such as (I had a hard time getting out of bed, I procrastinated, I feel motivated) do not show if the test-taker accomplished the task even when not motivated.

After factor analysis by the authors, 3 items were removed, leaving us with 27 items in total for this study's purpose, of which 14 items were reverse coded. To improve on the consistency of the response format, we adopted a rank order scale from 1-6 for all items, where 1 indicates low "energy" and 6 indicates high "energy" (for reverse items, it is the opposite). The English version was translated into Turkish by the present authors.

2.2.5 SHAPS

Snaith-Hamilton Pleasure Scale, originally published in 1995 [10], then modified in 2014, measures hedonic tone and anhedonia (pleasure and lack of pleasure) covering 4 domains of the hedonic experience, quality of life and satisfaction, social interaction, and sensory experience. For example: I enjoy seeing others smile, taking a hot shower, being around friends and family, etc. It consists of 14 items scaled from 1-4, with a maximum score of 56. Low scores on the SHAPS questionnaire imply lack of experiencing pleasure. The English version was translated into Turkish by the present authors.

2.3 Effortful Motivation measurement with b/a ratio

In mathematical terms, we let:
Pleasure (a) = a.
Compound (b) = a + e, where (e) is pure effort.
To obtain a value that describes effort, we have tried subtraction (e = b - a), and a ratio (b/a = (a+e)/a = 1 + e/a.) and found that the ratio is producing results that capture the intended effort value better. Therefore, the b/a value will be our measure of how much one is likely to put effort on something they find pleasurable.
A value of 1 (b/a = 1) implies that an action does not cost any effort (e = 0), A value less than 1 (b/a $<$ 1, e/a is negative) implies that one is less willing to put in the effort relative to the amount of pleasure the activity would provide. Meaning they find the activity pleasurable but not motivated to put in effort for it. And a value more than 1 (b/a $>$ 1, e/a is positive) implies that one will display effort even if they do not find the activity pleasurable. Meaning they are effortful.

2.4 Statistical Analysis

We chose non-parametric statistics due to the nature of questionnaire items, which reflect an ordinal level of measurement.

2.4.1 Reliability analysis

Using SPSS 25 software, we performed standard reliability tests (Cronbach-alpha) to measure the validated questionnaires and the novel HEFFORT items' internal consistency. This resulted in removing 4 items due to low Cronbach-alpha values.

2.4.2 Spearman Rank Correlation

For correlation between the variables, we employed the Spearman rank order correlation. We should notice that a correlation can mean that A causes B, B causes A, or both, or that the link is spurious, caused by a third variable.
We performed spearman rank test to explore correlations' strengths and direction in our dataset between the HEFFORT final effort-related motivation score and previous questionnaires' motivation items.
For each test, we chose to remove missing data instead of replicating or replacing it with gross means. The number of participants with valid b/a ratio scores was 272.

MATLAB was used for extracting means, standard deviation, and data visualization (histograms and scatter plots). Based on results from correlations, regressions, and histograms, we were able to assume validity of our results due to normality of the sample, reported in Figure 2.1., linearity, independence of results, as well as homogeneity of variances.

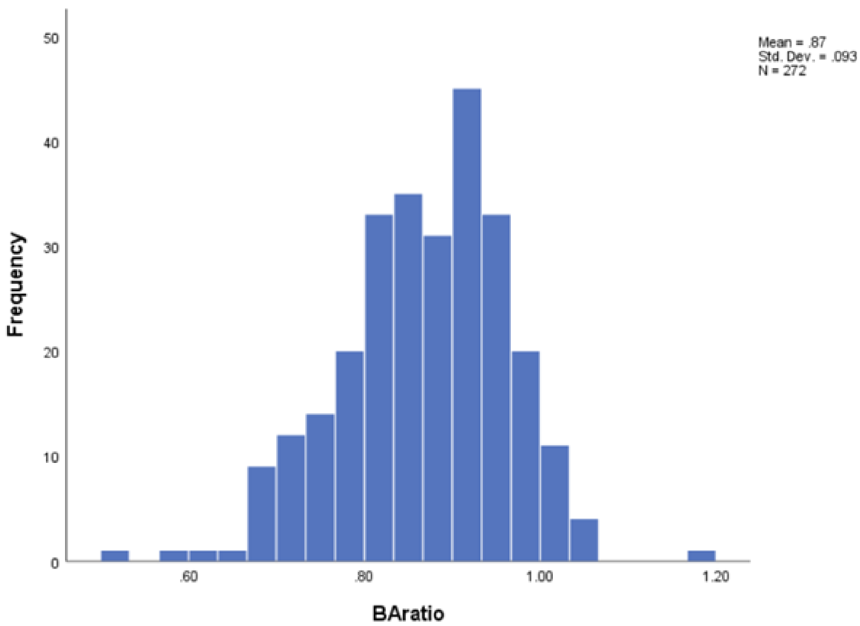

Figure 2.1 Demonstration of the normal distribution of b/a scores among all participants in the study.

2.4.3 Factor Analysis

In order to categorize HEFFORT's items into hedonic experiences, we ran factor analysis on HEFFORT (a) items. We chose varimax rotation method with eigenvalue = 1, and we suppressed coefficients smaller than 0.30. We also ran factor analysis on the other questionnaires items as well to confirm the categories determined by previous studies as well as determining if there are any correlations between HEFFORT and other questionnaires' categories.

2.5 Unsupervised Machine Learning Clustering

We applied k-means clustering algorithm to extract motivation levels from HEFFORT overall b/a score based on our mathematical model. We chose k-means clustering algorithm because it allows us to determine the number of clusters intended.
According to our mathematical model, we should obtain 3 motivation levels, high, low,

and moderate. Therefore, we chose k=3, and number of iterations = 10.

2.6 Supervised Machine Learning Classification and Regression

We considered decision tree classification to be most suitable to our data, due to its ability to handle both categorical and continuous observations.
In order to decide the best decision tree growing method, using IBM SPSS modeler, we ran the Auto-Numeric node to estimate and compare different tree models for our continuous dependent variable (b/a score) using different growing approaches in a single modeling run.
We chose Chi-squared Automatic Interaction Detection (CHAID) growth method for building our decision trees, because it showed higher correlation between the real and predicted b/a values in comparison with other growth methods.
For CHAID analysis, the first step is to determine the target or dependent variable, in our case it is the b/a score, which we consider the root when developing the decision tree. CHAID growing method uses chi-square statistics to identify optimal splits, where a chi-square (Xc) statistic estimates how the predicted results compare to the actual data using the following formula:

$$Xc^2 = \sum (Oi - Ei)^2/Ei$$

where
c = Degrees of freedom
O = Observed value
E = Predicted value

This growth method works by creating all possible cross tabulations for each predictor until the best outcome is achieved and no further splitting can be performed.

We ran CHAID Decision Tree classification using SPSS 25 to predict features of individuals with high and low scores on the b/a ratio scale of effortful motivation.

The features in our predictive model were participants' demographics, questionnaires' individual items, and total scores. We tried different combinations of these features to find the best predictors of the overall b/a score.

The DT process in SPSS assumes that all values at the dependent variable have defined value labels. Therefore, we used the clusters obtained from both the mathematical model and the k-means clustering to define b/a classes.

For the sake of dimensionality reduction, we ran Multiple Linear Regression (MLR) to reduce the number of variables included as input to the model without losing important information then reran the decision tree model based on MLR results.

As a final step to check our predictions' accuracy, we constructed a decision tree model by applying CHAID algorithm with the overall b/a score as the dependent variable, and different items as predictors in IBM SPSS Modeler 18.0. We first used HEFFORT items as input to our model, then we used different significant items obtained in the decision tree analyses as input.

2.7 Analysis Steps

To validate HEFFORT's psychometric properties and its ability to measure effortful motivation, as well as obtain predictors of one's motivation level, we implemented the following steps:

- Reliability analysis to demonstrate HEFFORT internal consistency.
- Spearman rank correlation to examine relationships between HEFFORT subscales and validated questionnaires' subscales and total scores.
- Factor analysis to categorize HEFFORT items according to hedonic experiences. Factor analysis extracts the maximum common variance from all the variables and puts them into a common score. Thus, reducing the large number of variables into fewer components.
- Implementing decision tree (DT) classification algorithm to determine all the

significant predictors of the overall b/a motivation score. Thereby providing information about the characteristics of individuals with different motivation levels.

- Applying multiple linear regression (MLR) to reduce the number of variables without losing important information. MLR assigns each variable (feature) a certain weight that quantifies the importance of this feature in predicting the overall b/a motivation score.
- Use MLR results as input to the DT algorithm for dimensionality reduction.
- Determine DT model accuracy in predicting b/a score based on different inputs.

Analysis steps are explained in Figure 2.2.

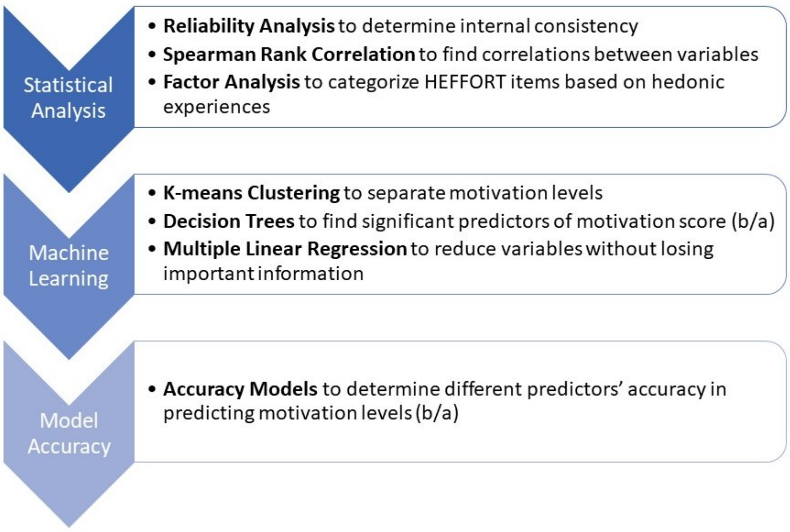

Figure 2.2 Analysis steps in the study.

3. RESULTS

3.1 Participants Demographics

Our recruited participants were 53.23% (191) male, 39.94% (131) female, and 6.83% (22) did not specify, as for their age, 39.94% (131) were in the 1st group (18-25), 20.42% (67) group (26-33), 12.19% (40) group (34-41), 8.53% (28) group (42-49), 8.84% (29) group (50-57), and 9.14% (30) in the oldest group (58-65+). The average of age is (33.81 years of age with 14.48 SD).

Participants were also separated based on income groups as follows: 10.06% (33) first group (0-1500), 15.54% (51) in the second group (1501-2500), 26.22% (86) in third group (2501-4000), 27.13% (89) in fourth group (4001-8000), and 16.15% (53) in the highest pay group (8001+). 8.84% (29) reported use of drugs, 89.93% (295) reported no use of drugs, with only one (0.3%) participant who did not specify. All demographical characteristics are listed in Table 3.1.

Table 3.1
Demographical characteristics for the recruited participants.

	Age Group	**Gender**	**Education**	**Income**	**Medicine**
N	325	323	325	312	325
Median	2	1	4	2501-4000	2
Std. Deviation	1.69692	0.497	0.954	1.222	0.305
25th percentile	1	1	3	2	2
50th percentile	2	1	4	3	2
75th percentile	4	2	4	4	2

3.2 Questionnaires Internal Consistency

Cronbach-alpha (coefficient of internal consistency) of HEFFORT final b/a score for all 33 items was 0.812, removing items (9,20,30,32) yielded an alpha value of 0.889 for 29 items. HEFFORT items prove internally consistent.
Cronbach-alpha for the comparison questionnaires are reported in Table 3.2.

Table 3.2
Reliability analysis results.

Questionnaire	**Cronbach-alpha value of all items**	**Alpha value**	**Items included**
HEFFORT	0.812, removing HEFFORT 9, 20, 30, 32	0.889	(29 items)
SHAPS:	0.714, removing SHAPS-12:	0.831	(13 items)
DARS:	0.894, removing DARS B9:	0.895	(16 items)
DARS-A:		0.947	(4 items)
DARS-B:	0.801, removing B9:	0.824	(3 items)
DARS-C:		0.786	(4 items)
DARS-D:		0.924	(5 items)
BDI:	0.865, removing BDI-19:	0.868	(20 items)
MEI:	0.754, removing 12, 16, 17R, 18R	0.866	(23 items)

3.3 Relationship Between HEFFORT and Previous Questionnaires' Total Scores and Subscales

We applied spearman rank correlation to observe relationships between HEFFORT and previously validated questionnaires. We found that the final HEFFORT score b/a representing the pure effort scale did not correlate with the pleasure (a) items in the HEFFORT questionnaire ($r<0.026$), and had high correlation with the effort and pleasure compound (b) items ($r=0.681$, $p<0.01$). b/a also correlated positively with DARS (C) social activity scale, DARS (D) sensory experiences scale, MEI's physical energy items and effortful social activity items, ($p<0.01$)
The pleasure (a) items in HEFFORT correlated highly with SHAPS hedonic pleasure

scale (r=0.522, p<0.01), as well as DARS (r=0.518, p<0.01). They also correlated negatively with BDI-IA depression scale (r=-0.093).
Thus, we concluded that our b/a score is a valid effortful motivation scale separate from pleasure.

As for the validated questionnaires we found DARS to correlate negatively with BDI (r=-0.138, p<0.05), and positively with SHAPS (r=0.401, p<0.01). MEI to correlate negatively with BDI (r=-0.563, p<0.01) and positively with SHAPS (r=0.134, p<0.05). These results are reported in Table 3.3.

Table 3.3
Spearman rank correlation test results.

		SHAPS sum	DARS sum	BDI sum	MEI sum	A Sum	B Sum	BA ratio
SHAPS	r.	1	.401**	-0.042	.134*	.522**	.443**	0.074
	p.		0	0.478	0.023	0	0	0.227
	n	320	301	287	287	288	283	269
DARS	r.	.401**	1	-.138*	0.076	.518**	.468**	.183**
	p.	0		0.021	0.208	0	0	0.003
	n	301	308	278	280	275	273	258
BDI	r.	-0.042	-.138*	1	-.563**	-0.093	-0.052	0.016
	p.	0.478	0.021		0	0.133	0.399	0.802
	n	287	278	294	265	264	261	248
MEI	r.	.134*	0.076	-.563**	1	.122*	0.108	0.084
	p.	0.023	0.208	0		0.047	0.081	0.182
	n	287	280	265	293	268	264	251
a sum	r.	.522**	.518**	-0.093	.122*	1	.684**	0.026
	p.	0	0	0.133	0.047		0	0.67
	n	288	275	264	268	291	272	272
b sum	r.	.443**	.468**	-0.052	0.108	.684**	1	.681**
	p.	0	0	0.399	0.081	0		0
	n	283	273	261	264	272	287	272
b/a	r.	0.074	.183**	0.016	0.084	0.026	.681**	1
	p.	0.227	0.003	0.802	0.182	0.67	0	
	n	269	258	248	251	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

**. Correlation is significant at the 0.05 level (2-tailed).

3.4 Categorizing Questionnaires Hedonic Experiences

3.4.1 HEFFORT Factor Analysis

In order to categorize HEFFORT's items into hedonic experiences, we ran factor analysis on HEFFORT a-items.

We chose principal component analysis (PCA) as an extraction method, varimax rotation method with eigenvalue = 1, and we suppressed coefficients smaller than .30. Scree plot is reported in Figure 3.1.

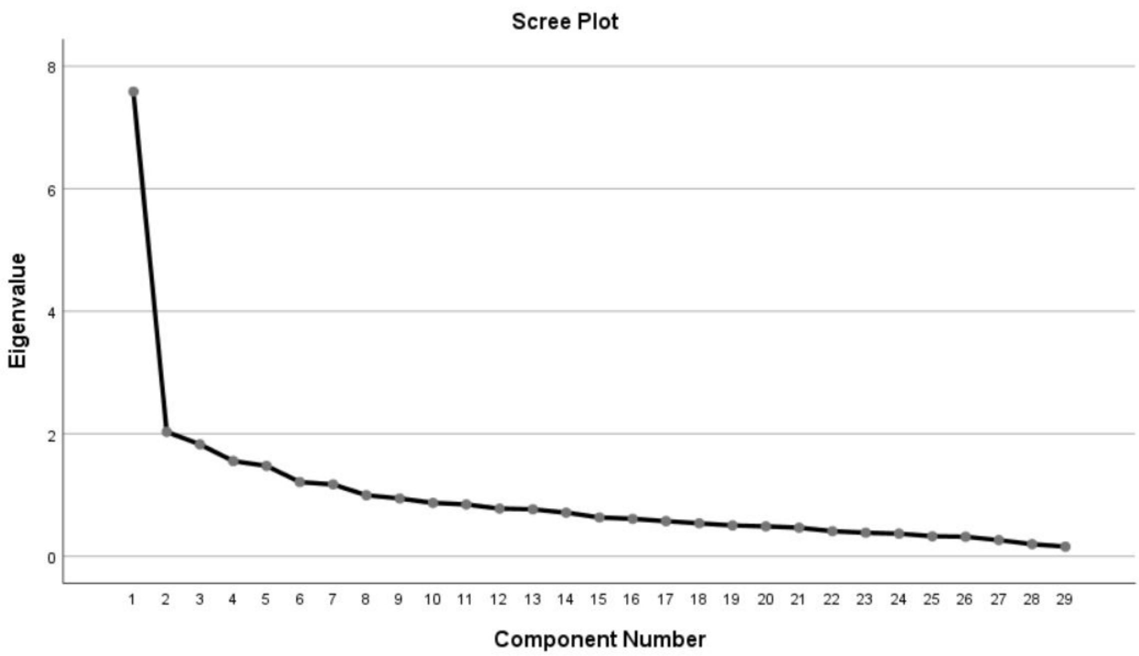

Figure 3.1 Factor analysis PCA scree plot.

We extracted 7 factors that accounted for 58.119% of the variance. Only 2 factors are above 10% of the variance. Components' variances are reported in Table 3.4. and Table 3.5.

We ended up with 7 components, and the items were distributed as following in Table 3.6.

We observe in Table 3.6. the items related to each component.

Note that (*) items load on only 1 component, while others load on 2 or more components.

Table 3.4
HEFFORT components initial eigenvalues.

Component	Total	% of Variance	Cumulative %
1	7.585	26.155	26.155
2	2.03	7	33.155
3	1.826	6.298	39.453
4	1.554	5.359	44.811
5	1.475	5.087	49.899
6	1.211	4.175	54.074
7	1.173	4.045	58.119

Table 3.5
Extraction and Rotation Sum of Square Loadings for HEFFORT's top components.

Extraction SSL			Rotation SSL		
Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
7.585	26.155	26.155	3.506	12.089	12.089
2.03	7	33.155	3.152	10.867	22.957
1.826	6.298	39.453	2.737	9.438	32.395
1.554	5.359	44.811	2.078	7.167	39.562
1.475	5.087	49.899	1.961	6.762	46.324
1.211	4.175	54.074	1.721	5.933	52.257
1.173	4.045	58.119	1.7	5.862	58.119

3.4.2 HEFFORT Components

Component 1: (social/self-care experiences)

- HEFF5a (3): I love kids
- HEFF7a (*): I love the seaside
- HEFF22a (2): love good food
- HEFF23a (*): I love fruits
- HEFF25a (*): I love home cooked food
- HEFF26a (3): love the sun
- HEFF27a (*): I love to see the sunrise

Items in this category reflect a form of hedonia one experiences while surrounded by others. Seaside means being surrounded by people, good food may reflect a restaurant where people are present, fruits may involve picking in a farm, home-cooked food is usually eaten with family, sun and sunrise are usually enjoyed with other people as well.

Component 2: (novelty/surprise items)

- HEFF2a (*): I love tasting new foods
- HEFF3a (*): I love animals
- HEFF4a (1)(3): love plants
- HEFF14a (1): I love nature
- HEFF15a (*): I love dogs

Table 3.6
Rotated matrix of extracted components.

	1	2	3	4	5	6	7
HEFF1a						0.653	
HEFF2a		0.501					
HEFF3a		0.775					
HEFF4a	0.358	0.487	0.379				
HEFF5a	0.484		0.439				
HEFF6a		0.318		0.34			
HEFF7a	0.563						
HEFF8a				0.638			
HEFF10a				0.748			
HEFF11a					0.857		
HEFF12a			0.815				
HEFF13a			0.336				0.659
HEFF14a	0.339	0.469					
HEFF15a		0.716					
HEFF16a	0.388	0.397				0.461	
HEFF17a					0.851		
HEFF18a	0.358	0.505				0.323	
HEFF19a			0.792				
HEFF21a		0.608	0.32				
HEFF22a	0.558	0.368					
HEFF23a	0.558						
HEFF24a						0.693	
HEFF25a	0.686						
HEFF26a	0.536		0.425				
HEFF27a	0.555						
HEFF28a							0.726
HEFF29a	0.444						0.495
HEFF31a	0.398		0.57				
HEFF33a				0.575			0.312

- HEFF18a (1)(6): I love music
- HEFF21a (3): I love art

Items in this category reflect internal hedonic experiences which entail a degree of novelty like surprises found in tasting new foods or new music or art, or through different animal behaviors.

Component 3: (easy/feel-good items)

- HEFF12a (*): I love people
- HEFF19a (*): I like people
- HEFF31a (1): I love to see people smileine

Items in this category involve smiling, happiness, and simple pleasures.

Component 4: (hygiene/self-care items)

- HEFF6a (2): I love to be surrounded by friends
- HEFF8a (*): I like hygiene
- HEFF10a (*): I like fit body types
- HEFF33a (7): I love new outfits

Items in this category indicate pleasures one gets from self-care and appealing to friends and others.

Component 5: (home items)

- HEFF11a (*): I love my home
- HEFF17a (*): I love my home

In this category, (a) items are the same, reflecting one's love of their home.

Component 6: (smell/taste items)

- HEFF1a (*): I love the taste of sweets
- HEFF16a (1) (2): I love food
- HEFF24a (*): I love bread

Items in this category include foods.

Component 7: (social-physical activities)

- HEFF13a (3): I love parties
- HEFF28a (*): I love swimming pools
- HEFF29a (1): I love sports

Items in this category include pleasure achieved by movement and being surrounded by others.

3.4.3 SHAPS factor analysis

We extracted 3 components above 10% of the variance. Total variance is explained in the hline. and Table 3.8. Our 3 components are separated according to the rotation component matrix reported in Table 3.9.

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.607	35.441	35.441
2	1.256	9.66	45.101
3	1.102	8.476	53.577

Table 3.7
SHAPS components initial eigenvalues.

Table 3.8
Extraction and Rotation sum of squared loadings for SHAPS's top components

Extraction SSL			Rotation SSL		
Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
4.607	35.441	35.441	3.268	25.14	25.14
1.256	9.66	45.101	2.217	17.057	42.197
1.102	8.476	53.577	1.479	11.38	53.577

Table 3.9
SHAPS rotated component matrix.

Component	1	2	3
SHAPS1		0.584	0.346
SHAPS2		0.76	
SHAPS3		0.773	
SHAPS4	0.368	0.567	
SHAPS5	0.579		
SHAPS6	0.686		
SHAPS7	0.729		
SHAPS8			0.739
SHAPS9	0.589		
SHAPS10	0.601	0.352	
SHAPS11	0.72		
SHAPS13	0.614	0.31	
SHAPS14			0.824

3.4.4 SHAPS Components

Component 1:

- SHAPS7 (*): I would enjoy seeing other people's smiling faces
- SHAPS11 (*): I would find pleasure in small things; e.g. bright sunny day
- SHAPS6 (*): I would find pleasure in the scent of flowers or the smell of a fresh sea breeze
- SHAPS13 (2): I would get pleasure from helping others
- SHAPS10 (2): I would enjoy a cup of tea or coffee or my favorite drink
- SHAPS9 (*): I would enjoy reading a book, magazine or newspaper
- SHAPS5 (*): I would enjoy a warm bath or refreshing shower

Items in this category reflect simple pleasures.

Component 2:

- SHAPS3 (*): I would find pleasure in my hobbies and pastimes
- SHAPS2(*): I would enjoy being with family or close friends
- SHAPS1 (3): I would enjoy my favorite television or radio program
- SHAPS4 (1): I would be able to enjoy my favorite meal

Items in this category reflect activities to be enjoyed in familiar atmospheres.

Component 3:

- SHAPS14 (*): I would feel pleasure when I receive praise from other people
- SHAPS8(*): I would enjoy looking smart when I have made an effort with my appearance

Items in this category reflect enjoying external appraisal to feel good about oneself.

3.4.5 BDI Factor Analysis

We extracted 4 components above 10% of the variance. Total variance is explained in Table 3.10. and Table 3.11.
Our 4 components are separated according to the rotation component matrix reported in Table 3.12.

Table 3.10
BDI components initial eigenvalues.

Component	Total	% of Variance	Cumulative %
1	6.02	30.099	30.099
2	1.419	7.096	37.195
3	1.156	5.78	42.974
4	1.09	5.45	48.424

Table 3.11
Extraction and Rotation Sum of Square Loadings for BDI's top components.

Extraction SSL			Rotation SSL		
Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
6.02	30.099	30.099	2.751	13.754	13.754
1.419	7.096	37.195	2.475	12.374	26.128
1.156	5.78	42.974	2.243	11.215	37.343
1.09	5.45	48.424	2.216	11.081	48.424

3.4.6 BDI Components

Component 1:

- BDI1 (*): Feeling sad
- BDI2 (4): Discouraged about future
- BDI3 (2): Feeling like a failure

Table 3.12
BDI rotated component matrix.

Component	1	2	3	4
BDI1	0.636			
BDI2	0.565			0.37
BDI3	0.542	0.46		
BDI4	0.3		0.341	0.381
BDI5	0.656			
BDI6	0.678			
BDI7	0.627	0.485		
BDI8	0.306		0.674	
BDI9			0.523	
BDI10			0.341	0.36
BDI11		0.498		
BDI12		0.452	0.378	0.335
BDI13		0.576	0.375	
BDI14		0.505	0.414	
BDI15			0.616	0.337
BDI16				0.609
BDI17		0.498	0.317	0.488
BDI18				0.673
BDI20		0.649		
BDI21				0.578

- BDI5 (*): Feeling guilt
- BDI6 (*): Feeling punishment
- BDI7 (2): Feeling disappointed

Items in this category reflect negative feelings about oneself or psychological pain

Component 2:

- BDI11 (*): Feeling irritated
- BDI12 (3) (4): Losing interest in people
- BDI13 (3): Making decisions
- BDI14 (3): Self-image, looking attractive
- BDI17 (3) (4): Getting tired
- BDI20 (*): Worrying about health

This component is a cognitive-emotive factor. Items in this category reflect feelings related to decision-making, worrying, fidgeting about one's looks, being irritated about things/events.

Component 3:

- BDI8 (1): Self-criticizing
- BDI9 (*): Suicidal thoughts
- BDI15 (4): Putting effort to do something

Items in this category reflect self-loathing and feelings of insufficiency.

Component 4:

- BDI4 (1) (3): Feeling satisfied
- BDI10 (3):Crying

Items in this category reflect sadness and failure [14].

3.4.7 DARS Factor Analysis

DARS is already categorized [1] into 4 categories (hobbies/pastime, Foods/Drinks, Social activities, Sensory experiences). We applied factor analysis to see if our data matches previous results.
Our rotated component matrix reported in Table 3.13. validates previous categorizing of DARS items.

Table 3.13
DARS rotated component matrix.

Component	1	2	3	4
DarsA1		0.882		
DarsA2		0.909		
DarsA3		0.931		
DarsA4		0.885		
DarsB6				0.822
DarsB7				0.854
DarsB8				0.805
DarsC11		0.306	0.736	
DarsC12			0.765	
DarsC13			0.688	
DarsC14			0.736	
DarsD16	0.801			
DarsD17	0.856			
DarsD18	0.861			
DarsD19	0.871			
DarsD20	0.859			

We have also applied factor analysis to both DARS and HEFFORT together to see if there is any link between questionnaires' components.
We found a clear separation between DARS and HEFFORT components.

Table 3.14
HEFFORT with DARS rotated component matrix.

Component	1	2	3	4	5	6	7	8	9	10	11
DarsA1			0.859								
DarsA2			0.895								
DarsA3			0.929								
DarsA4			0.897								
DarsB6						0.826					
DarsB7						0.797					
DarsB8						0.687					
DarsC11				0.7							
DarsC12				0.691							
DarsC13				0.646							
DarsC14				0.725							
DarsD16		0.745									
DarsD17		0.839									
DarsD18		0.823									
DarsD19		0.859									
DarsD20		0.848									
HEFF1a										0.642	
HEFF2a		0.428			0.432						
HEFF3a					0.751						
HEFF4a	0.565				0.316						
HEFF5a	0.609										
HEFF6a	0.367			0.329							
HEFF7a	0.591										
HEFF8a									0.622		

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Component	1	2	3	4	5	6	7	8	9	10	11
HEFF10a									0.731		
HEFF11a							0.842				
HEFF12a	0.424							0.715			
HEFF13a								0.595			0.372
HEFF14a	0.551				0.34						
HEFF15a					0.739						
HEFF16a	0.339				0.349					0.44	
HEFF17a							0.826				
HEFF18a	0.386				0.463						
HEFF19a	0.39							0.738			
HEFF21a	0.326				0.492						
HEFF22a	0.556										
HEFF23a	0.388									0.312	
HEFF24a										0.689	
HEFF25a	0.611										
HEFF26a	0.648										
HEFF27a	0.569										
HEFF28a											0.693
HEFF29a	0.301										0.629
HEFF31a	0.616							0.333			
HEFF33a									0.551		0.349

3.4.8 MEI Factor Analysis

MEI is also categorized [9] into 3 categories (Mental energy, Physical energy, Social motivation). We applied factor analysis to MEI items, and found 5 categories instead of 3. Rotated component matrix is reported in Table 3.15.

Table 3.15
MEI rotated component matrix.

Component	1	2	3	4	5
MEI1P				0.799	
MEI2M				0.722	
MEI3RM			0.664		
MEI4RP			0.733		
MEI5RM	0.426		0.651		
MEI6RM	0.602		0.461		
MEI7RM	0.549		0.55		
MEI8RM	0.655				
MEI9RM	0.636		0.428		
MEI10RM	0.686		0.347		
MEI11RS	0.771				
MEI13S	-0.731				
MEI14RM	0.828				
MEI15RM	0.785				
MEI19RP				-0.649	
MEI20RP				-0.662	-0.343
MEI21S					0.643
MEI22S					0.76
MEI23S				0.316	0.631
MEI24P				0.356	0.385
MEI26S		0.693			
MEI27S		0.786			
MEI28S		0.81			
MEI29S		0.778			
MEI30S		0.508			0.553

We explored the factor structure of the revised MEI using the maximum likelihood method of extraction with varimax rotation. We forced the model onto three factors, in accordance with the three sub-scales of the MEI that aim to measure mental, physical, and social motivation. These components are reported in Table 3.16.

Table 3.16
MEI forced 3 factors' rotated component matrix.

Component	1	2	3
MEI1P		0.66	
MEI2M		0.632	
MEI3RM	0.54	0.301	
MEI4RP	0.573		
MEI5RM	0.68		
MEI6RM	0.742		
MEI7RM	0.75		
MEI8RM	0.719		
MEI9RM	0.769		
MEI10RM	0.765		
MEI11RS	0.728		
MEI13S	-0.558		-0.383
MEI14RM	0.811		
MEI15RM	0.779		
MEI19RP		-0.716	
MEI20RP		-0.709	
MEI21S			0.576
MEI22S			0.601
MEI23S		0.471	0.463
MEI24P		0.462	
MEI26S		0.619	
MEI27S		0.647	
MEI28S		0.661	0.376
MEI29S		0.622	0.39
MEI30S		0.305	0.638

3.4.9 MEI Components

Component 1:

- MEI3RM (2): have trouble getting out of bed in the morning for not wanting to face the day
- MEI4RP: run out of energy before the end of the day
- MEI5RM: have trouble finishing things you started because you lost interest in them
- MEI6RM: feel overwhelmed even by small tasks
- MEI7RM: procrastinate or put things off until another day
- MEI8RM: have trouble remembering information
- MEI9RM: have problems concentrating
- MEI10RM: have trouble making minor decisions
- MEI11RS: avoid social conversations with others
- MEI13S (3): prefer to be alone
- MEI14RM: have trouble focusing your attention on your work or other activities
- MEI15RM: have trouble keeping things organized

Items in this category reflect the majority of mental energy subscale items.

Component 2:

- MEI1P: feel enthusiastic when you began your day
- MEI2M: feel satisfied with what you accomplished during the day

- MEI3RM (1): have trouble getting out of bed in the morning for not wanting to face the day
- MEI19RP: feel energetic
- MEI20RP: feel motivated
- MEI23S (3): engage in recreational activities or hobbies
- MEI24P: exercise (like walking, swimming, etc)
- MEI26S: interested in taking on additional tasks or projects
- MEI27S: interested in learning or trying new things
- MEI28S (3): interested in meeting new people
- MEI29S (3): interested in talking with others
- MEI30S (3): interested in social activities like visiting friends, going out to dinner, or parties.

Items in this category cover all the physical subscale of MEI, as well as social and mental activities requiring physical effort.

Component 3:

- MEI21S: call, e-mail, or write letters to friends or family members
- MEI22S: get together with friends or family members who don't live with you
- MEI23S (2): engage in recreational activities or hobbies
- MEI28S (2): interested in meeting new people
- MEI29S (2): interested in talking with others
- MEI30S (2): interested in social activities like visiting friends, going out to dinner, or parties.

Items in this category cover all the social items on the social subscale in MEI.

We have also applied factor analysis to both MEI and HEFFORT together to see if there is any link between questionnaires' components. We found a clear separation between MEI and HEFFORT components. Rotated component matrix is reported in Table 3.17.

Table 3.17
MEI and HEFFORT rotated component matrix.

Comp.	1	2	3	4	5	6	7	8	9	10	11	12	13
MEI1P				.594									
MEI2M			.32	.525									
MEI3RM	.399											.601	
MEI4RP	.433											.664	
MEI5RM	.599											.423	
MEI6RM	.729												
MEI7RM	.712												
MEI8RM	.727												
MEI9RM	.765												
MEI10RM	.781												
MEI11RS	.75												
MEI13S	-.582												
MEI14RM	.837												
MEI15RM	.812												
MEI19RP				-.715									
MEI20RP				-.71									
MEI21S							.696						
MEI22S				.362			.63						
MEI23S							.623						
MEI24P				.438					.471				.357
MEI26S			.719										

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Comp.	1	2	3	4	5	6	7	8	9	10	11	12	13
MEI27S			.79										
MEI28S			.77										
MEI29S			.71										
MEI30S			.43				.52						
HEFF1a		.33		-.34			.33						
HEFF2a													-.57
HEFF3a						.73							
HEFF4a						.49					.49		
HEFF5a											.68		
HEFF6a		.41											-.31
HEFF7a		.65											
HEFF8a									.53				
HEFF10a									.72				
HEFF11a								.77					
HEFF12a					.77								
HEFF13a			.32							.52			
HEFF14a		.42			.31	.42							
HEFF15a						.79							
HEFF16a		.69											-.35
HEFF17a								.81					
HEFF18a		.68											
HEFF19a					.77								
HEFF21a		.33	.33			.46							
HEFF22a		.73											
HEFF23a		.55											
HEFF24a								.39	-.36				
HEFF25a		.66											
HEFF26a		.42			.51								
HEFF27a		.56											
HEFF28a										.78			
HEFF29a									.41	.59			
HEFF31a		.38			.49						.37		
HEFF33a					.33				.48	.37			

3.5 Clustering Motivation Levels

We applied k-means clustering algorithm with k=3 on the overall motivation b/a score to define our 3 motivation levels, high, low, and moderate.
In the initial cluster we found the centroids of our 3 clusters to be:
Cluster 1 centroid (Low motivation): b/a = 0.53
Cluster 2 centroid (High motivation): b/a = 1.18
Cluster 3 centroid (Moderate motivation): b/a = 0.85

After 10 iterations based on the means of the data points in each cluster we obtained the following centroids:
Cluster 1 centroid (Low motivation): b/a = 0.63
Cluster 2 centroid (High motivation): b/a = 1.05
Cluster 3 centroid (Moderate motivation): b/a = 0.87
Maximum and minimum points in the clusters are reported in Table 3.18. Data points in each cluster are reported in Figure 3.2.

Table 3.18
Motivation clusters minimum and maximum points.

	Minimum	Maximum	Number of cases in cluster
Cluster 1	0.53	0.69	7
Cluster 2	1.01	1.18	10
Cluster 3	0.7	1	255

We obtained 3 clusters based on our mathematical model. However, due to the low number of cases in the high and low motivation clusters, we seperated the moderate motivation level into "moderately low" and "moderately high" for better analysis.
Our moderate motivation level cluster centroid is b/a = 0.869. Therefore, we split the moderate motivation cluster to the following:
Moderately low: $0.7 < b/a < 0.869$
Moderately high: $0.87 < b/a < 1$

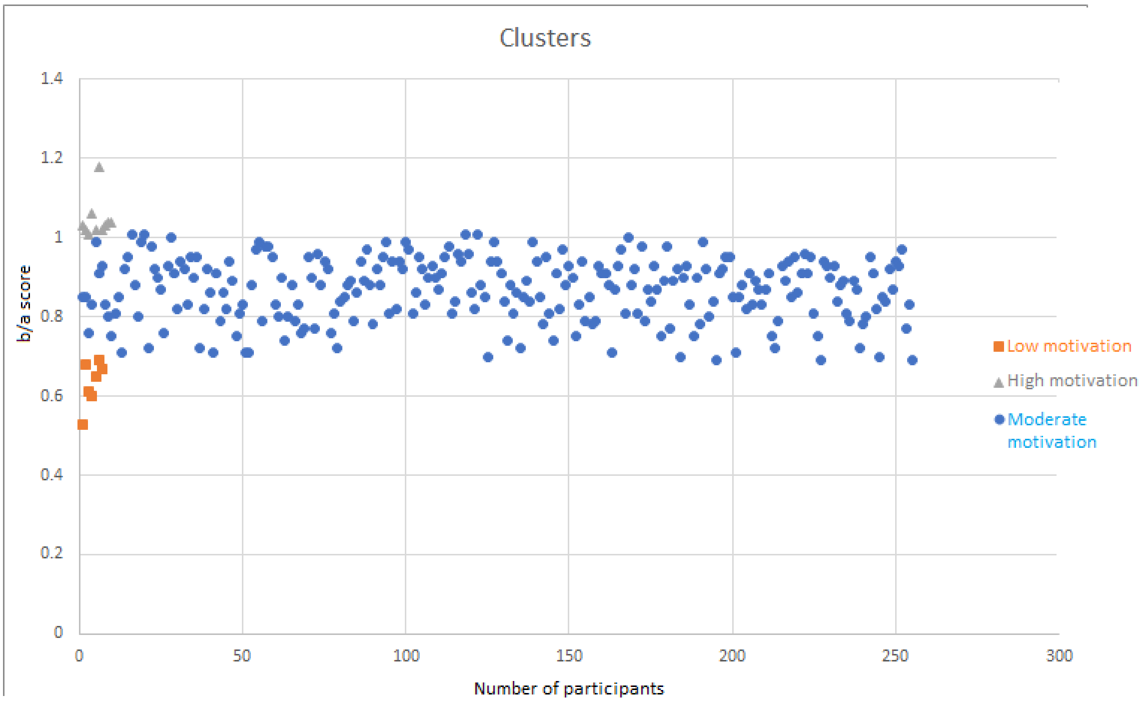


Figure 3.2 Data points in each cluster.

3.6 Decision tree results

In order to determine the best predictors of the overall b/a score, we implemented decision tree algorithms with different questionnaires' items as features. Our motivation levels were based on the mathematical model and the k-means clustering results.

3.6.1 Decision tree results of all items

1st iteration

We implemented DT algorithm on all the questionnaire (DARS, MEI, BDI, SHAPS, and HEFFORT) items to determine the most significant overall b/a score (motivation level) predictors.
The most significant predictor of the overall b/a score is item HEFFORT 25b/a (making home-cooked food). In turn, HEFFORT 25b/a splits the overall b/a score into 4 nodes in the second layer.
Participants with the least motivation to prepare home-cooked food (HEFFORT 25b/a <=0.2) were best predicted by item HEFFORT 15b (dog training). Those not willing to train dogs (HEFFORT 15b <=1) were better predicted by HEFFORT 8a (liking hygiene). We speculate that people who have low motivation levels are not willing to train dogs which may contradict with a clean environment they like. Maintaining such an environment will require effort they lack in the first place. On the other hand, those who were willing to train dogs were predicted by MEI 6 (overwhelmed by small tasks), indicating that willingness to train dogs depends on how quickly a person gets overwhelmed with small tasks.
All these features are predictors of moderate 'relatively low' motivation level (0.66 < b/a <0.77). Participants less overwhelmed by small tasks (MEI6 <=2) had better motivation score (predicted b/a = 0.84).

By contrast, participants with moderate motivation to prepare home-cooked

food (0.2< HEFFORT b/a25 < 0.5) were better predicted by MEI 19 (feeling energetic), indicating that physical energy is linked to moderate motivation. We can see from the third layer splits that people feeling less energetic (MEI19 <=2) were better predicted by HEFFORT 16b (I love cooking) a compound of both pleasure and effortful motivation. Participants with higher score on this item (HEFFORT 16b >3) were predicted to have a higher motivation level (b/a =0.94). On the other hand, those feeling more energetic (MEI19 >2) were better predicted by an effort item HEFFORT 23b/a (preparing smoothies), indicating that preparing smoothies requires more energy than cooking.
All features in this branch are predictors of moderate motivation level.

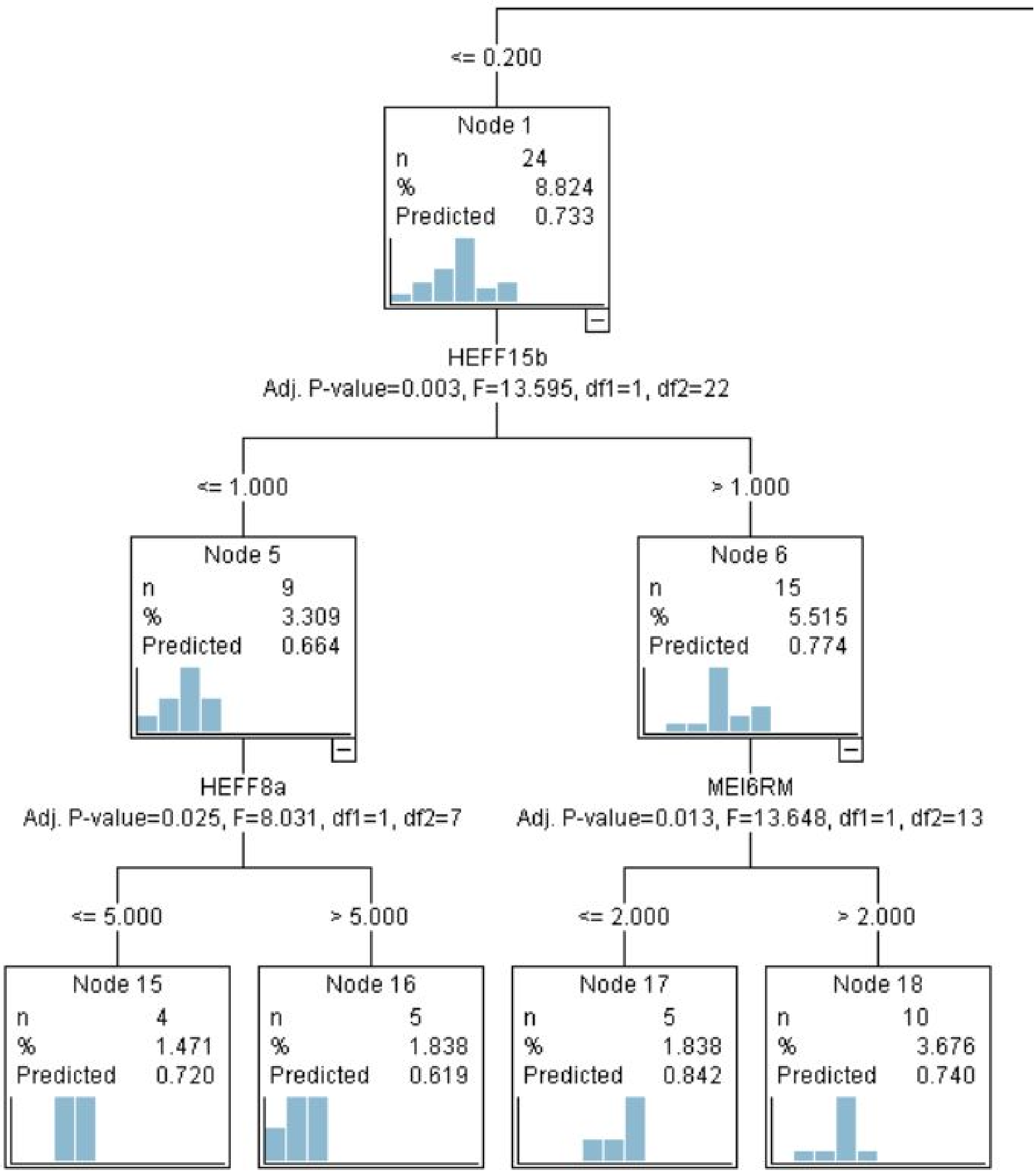
Participants with higher motivation scores (0.5 < HEFFORT b/a25 <0.83) were better predicted by HEFFORT 1b (walking to buy sweets), clearly indicating that people with higher motivation are more likely to exert effort on buying sweets. Those less interested in walking to buy sweets (HEFFORT 1b <=1) were distinguished by their willingness to participate in social events (DARS 14). On the other hand, those with higher interest in walking to buy sweets (1< HEFFORT 1b <5) were better predicted with HEFFORT b15 (dog training). While those with the highest motivation to walk to buy sweets (HEFFORT 1b >5) had the highest b/a score (predicted b/a = 0.94).

Finally, participants with the highest motivation score (HEFFORT b/a25 >=0.83) were best predicted by HEFFORT 22b/a (taking cooking classes). We speculate that the last two results (making home cooked food and taking cooking classes), describing higher motivation, are due to the actions (cooking and learning) being demanding of cognitive, social, and physical effort.

Again, participants with higher motivation but not interested in taking cooking classes (HEFFORT 22b/a <=0.2) are more likely to enjoy home cooked food (HEFFORT 25a), thus, enjoy familiarity. However, lower scores on this item (HEFFORT 25a <=4) predicted higher motivation (b/a =0.94).
On the other hand, those more willing to take cooking classes (0.2< HEFFORT 22b/a

<0.83, and $>=0.83$) were better predicted by HEFFORT 27b/a (waking up to see sunrise) and HEFFORT 26b/a (spending time under the sun), two effortful activities. Comparing the number of people enjoying the sunrise (HEFFORT 27a $> 5 = 202$) to those actually willing to wake up for it (HEFFORT 27b/a $> 5 = 101$) we can conclude that the action is quite effortful. Also, these two actions are related to freshness or novelty, and can directly be connected to the willingness to take cooking classes which also involves a level of novelty. These items are predictors of the highest motivation level ($0.91 <=$ b/a $<= 1.03$).

These observations indicate that HEFFORT b/a items, which measure effortful motivation regardless of the hedonic experience related to it, are better predictors of the overall b/a motivation score, especially high b/a scores. These items tend to describe energetic actions, and require physical or cognitive effort or even both. We can also see that MEI items show up in the tree, therefore, are successful predictors of the total b/a motivation score. We expected this since MEI is a measurement of energy.
Predictor items and cut-off results are reported in the DT branch in Figure 3.3.



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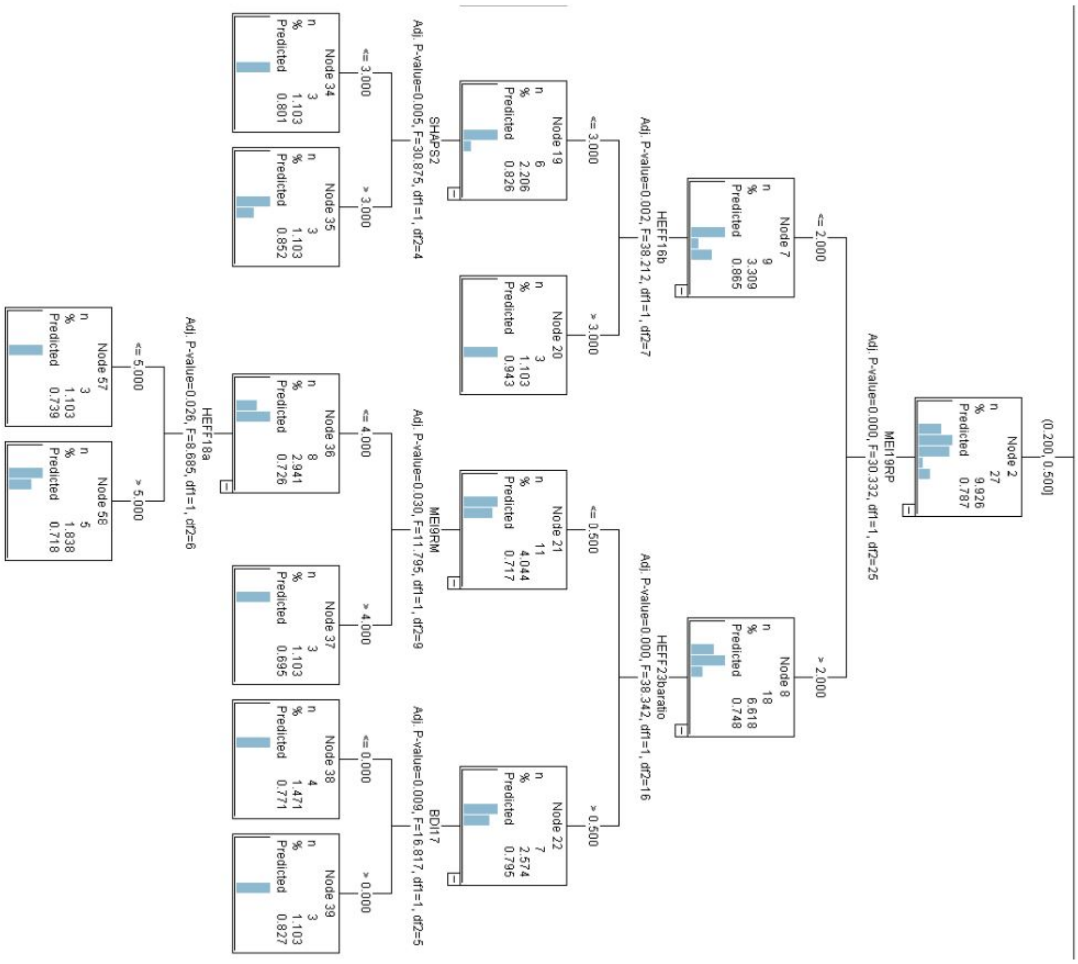

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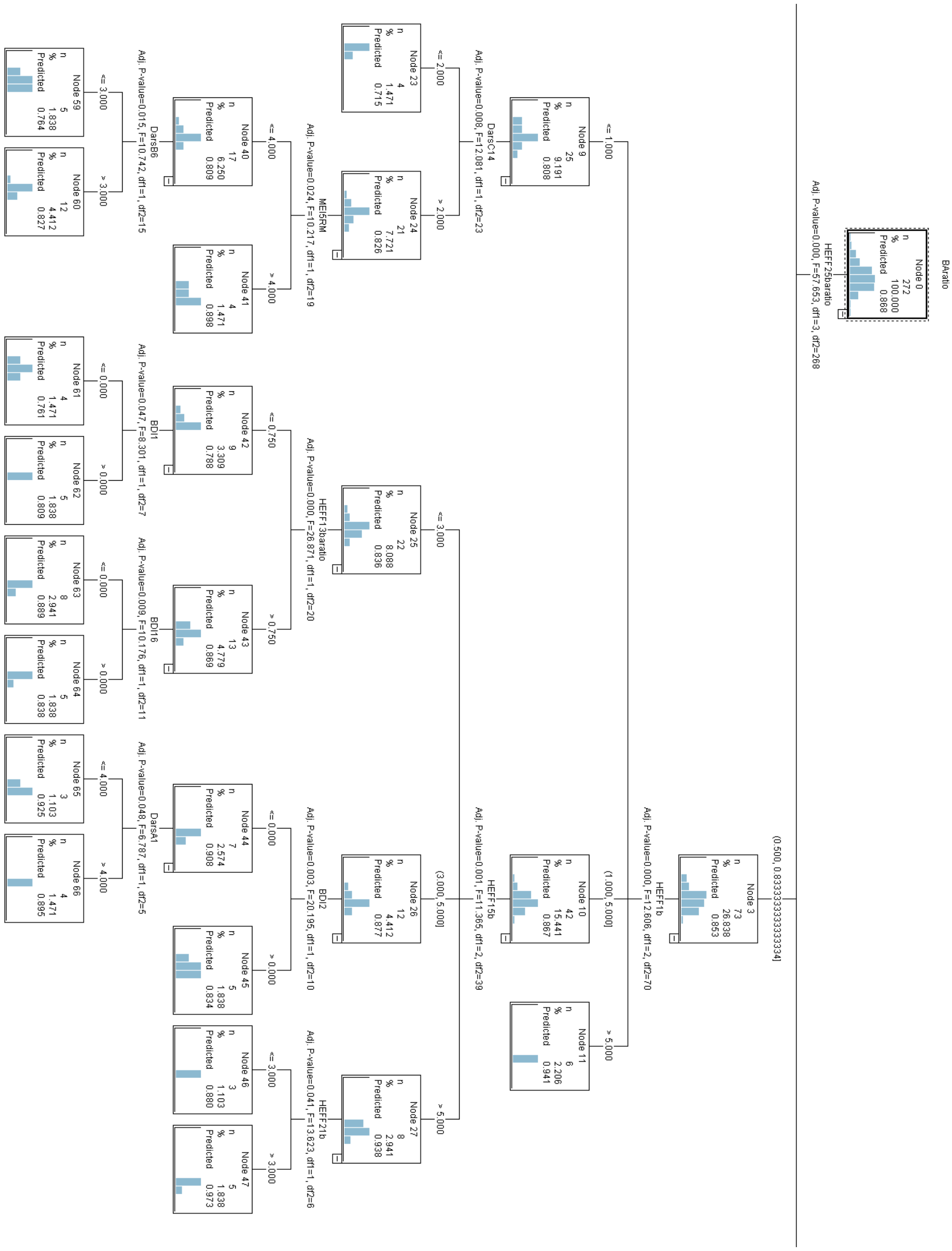

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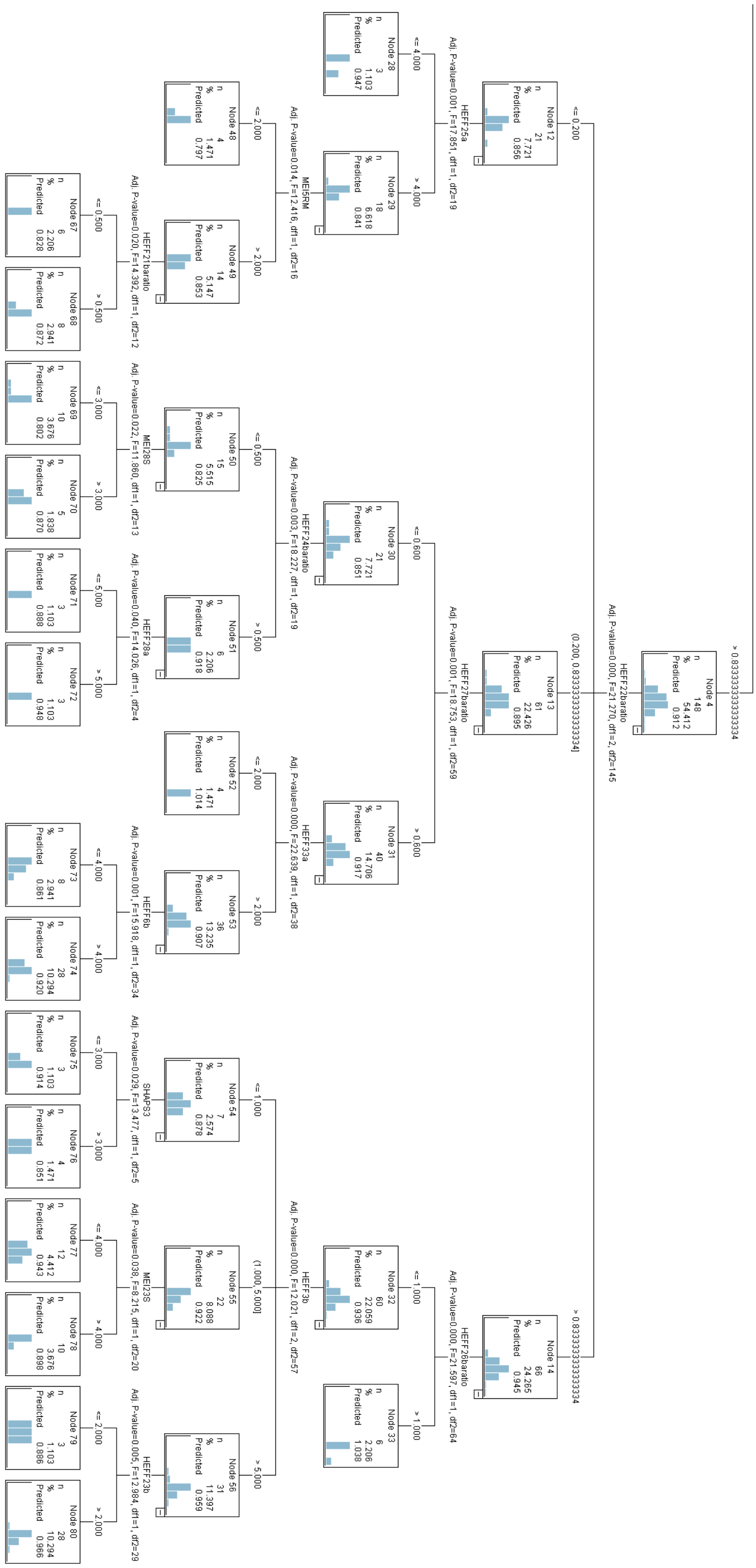


Figure 3.3 DT results of all items predicting motivational-effort scale from left to right.

2nd iteration

Since b/a items were dominant in the primary nodes of the first iteration, the b/a subscale was removed in the second iteration. In this iteration, the most significant predictor of the overall b/a score is item HEFFORT 25b (making home-cooked food). It splits the overall b/a score into 4 nodes in the second layer.

Participants who do not prefer to make home-cooked food (HEFFORT 25b <=1.0) were best predicted by item HEFFORT 1a (I love the taste of sweets). Those not fond of sweet tastes (HEFFORT 1a <=2) were better predicted by HEFFORT 28b (I love to swim in pools). Additionally, participants with a high score on the swimming item (HEFFORT 28b > 5) have a moderately high motivation level (predicted b/a = 0.94). Thus, people that enjoy a physical activity do not enjoy sweets as much but have higher motivation. On the other hand, those who enjoy the taste of sweets (HEFFORT 1a >2) were predicted by HEFFORT 15b (I love to train dogs), indicating that a person's love of tasting sweets is connected to their love of playing with dogs. Both activities linked to novelty of tasting something new or observing new behaviors through training animals.
Items in this branch (HEFFORT 1a >2) predict particularly low motivation in general.

By contrast, participants who somewhat enjoy making home-cooked food (1< HEFFORT b25 < 4) were better predicted by HEFFORT 29b (love doing sports), confirming the past analysis that physical energy links to moderate motivation. Those who love doing sports less (HEFFORT 29b <=3) were better predicted by DARS D20 (make an effort to spend time having sensory experience) and had moderately low motivation (b/a = 0.76), whereas those who love doing sports more (HEFFORT 29b >3) were better predicted by HEFFORT 2b (making new food), a novelty item, and had higher motivation (b/a = 0.87). We speculate that those who care about maintaining a healthy body by doing sports are more willing to make new foods to help them maintain a healthy diet as well. Those that do not prefer making new foods love bread, whereas those with intermediate love of food, and those that prefer making new foods love home cooked food.

In the deeper layers, we found participants who do not enjoy making new foods (HEFFORT 2b $<=$2) to be better predicted by HEFFORT 24a (I love bread), and those who moderately enjoy making new foods (2$<$ HEFFORT 2b $<=$3) were predicted by HEFFORT 16a (I love food), both food items. On the other hand, those who highly enjoy making new foods (HEFFORT 2b $>$3) were better predicted by HEFFORT 25a (I love home cooked food), an item belonging to social/self-care experiences. Hence, we find a link between higher motivation to do novel items and social/self-care experiences.

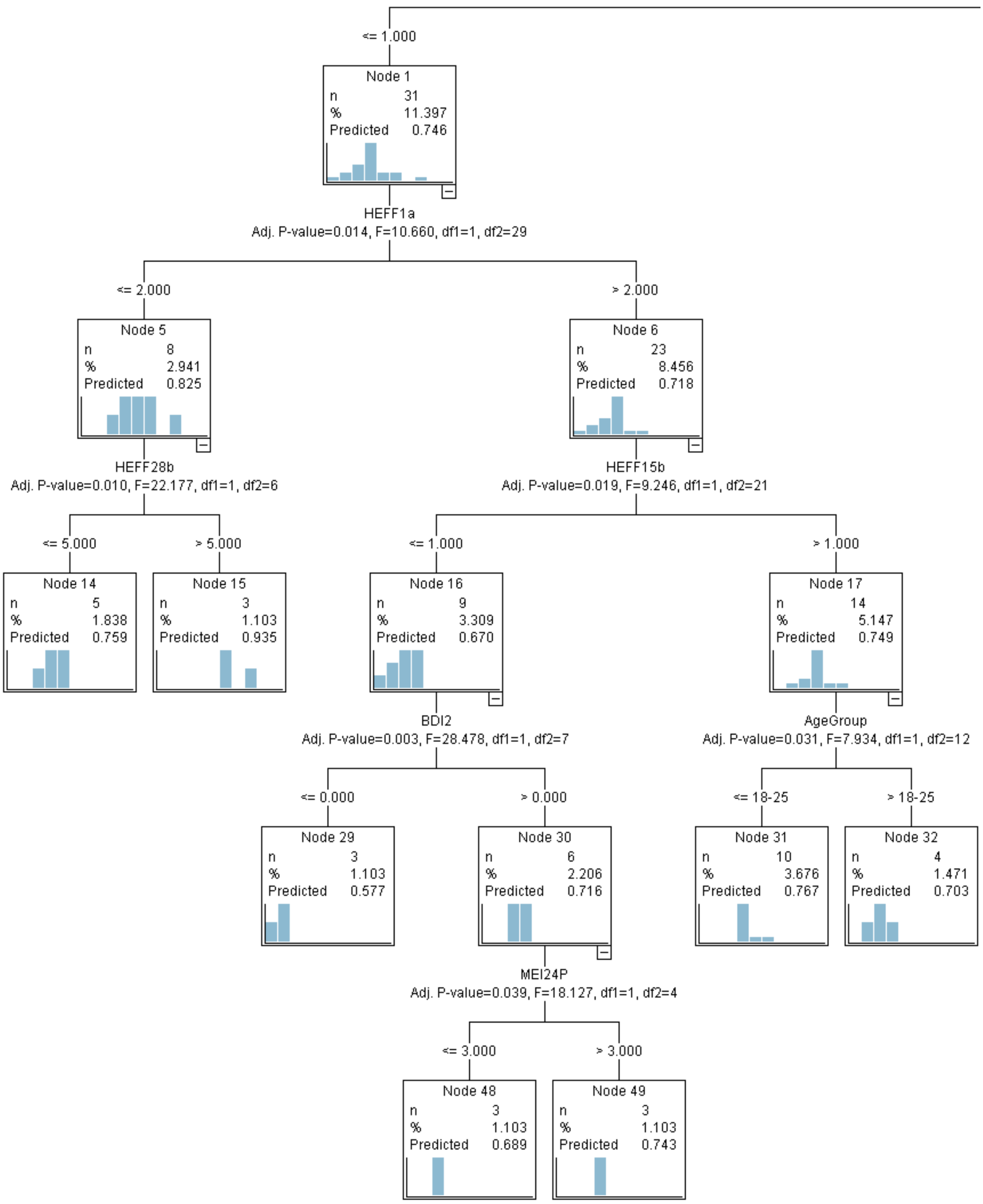
Participants who enjoy making home-cooked food (4 $<$ HEFFORT b25 $<$5) were better predicted by HEFFORT 26b (love spending time under the sun), possibly indicating that these items share a liking of social/self-care experiences or social situations. In line with this idea, those who most love spending time under the sun (HEFFORT 26b $>$2) were distinguished by their willingness to take cooking classes (HEFFORT 22b), again a social experience. Alternatively, these two activities may be linked to freshness and novelty. In addition, participants who love spending time under the sun (HEFFORT 26b $>$2) also have higher motivation (b/a = 0.89) compared to those who do not (b/a = 0.74).

Finally, participants who very much enjoy making home-cooked food (HEFFORT b25 $>$5) were best predicted by HEFFORT 26a (I love the sun) and have moderately high motivation (b/a = 0.92). Participants who somewhat love the sun (2$<$ HEFFORT 26a $<=$5) are further distinguished by their willingness to make bread themselves (HEFFORT 24b). The higher the will to make bread (HEFFORT 24b $>$ 4) the higher the motivation level (b/a = 1.01), whereas those who enjoy sun the most were better predicted by their willingness to take cooking classes (HEFFORT 22b).

In the first iteration, we included effort (b/a) items, whereas in the second we removed them. Comparing the first and second iteration results, we observe that the best predictor of effortful motivation (i.e. overall b/a ratio) is linked to a willingness (25b/a) or love of making home-cooked food (25b) and a willingness to take cooking classes. We speculate that taking cooking classes, which requires cognitive, physical, and social motivation, is tightly linked to high motivation.

These observations indicate that HEFFORT b items, which measure a compound of pleasure and effortful motivation, are second-best at predicting the overall b/a motivation score. These items tend to describe energetic actions, and require physical or cognitive effort or even both. We can also see that DARS sensory items show up in the tree, therefore, are successful predictors of the total b/a motivation score. We expected this since DARS measures desire, motivation, effort and consummatory pleasure across hedonic domains, similar to HEFFORT's b items representing a compound of pleasure and effort.

The age variable was also a significant predictor in the deeper nodes, with people in the first (18 - 25 years) and third (34 - 41 years) age groups having higher motivation than other age groups, (predicted b/a = 0.92 and b/a = 0.97 respectively). In addition, gender was a significant predictor with females having higher motivation (b/a = 0.98) than males (b/a = 0.89). Significant predictors and cut-off results are reported in figures[3.4] from left to right.



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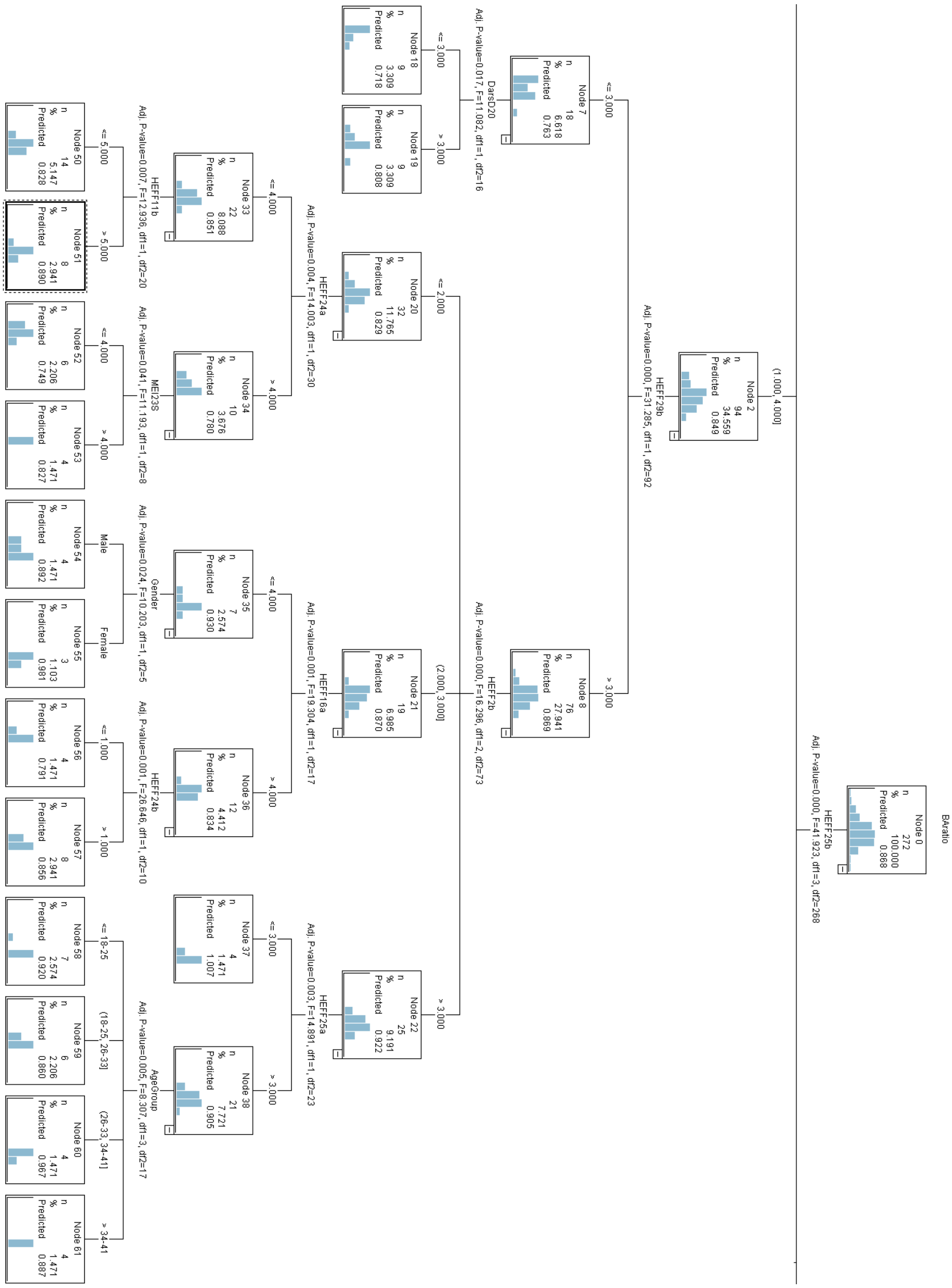

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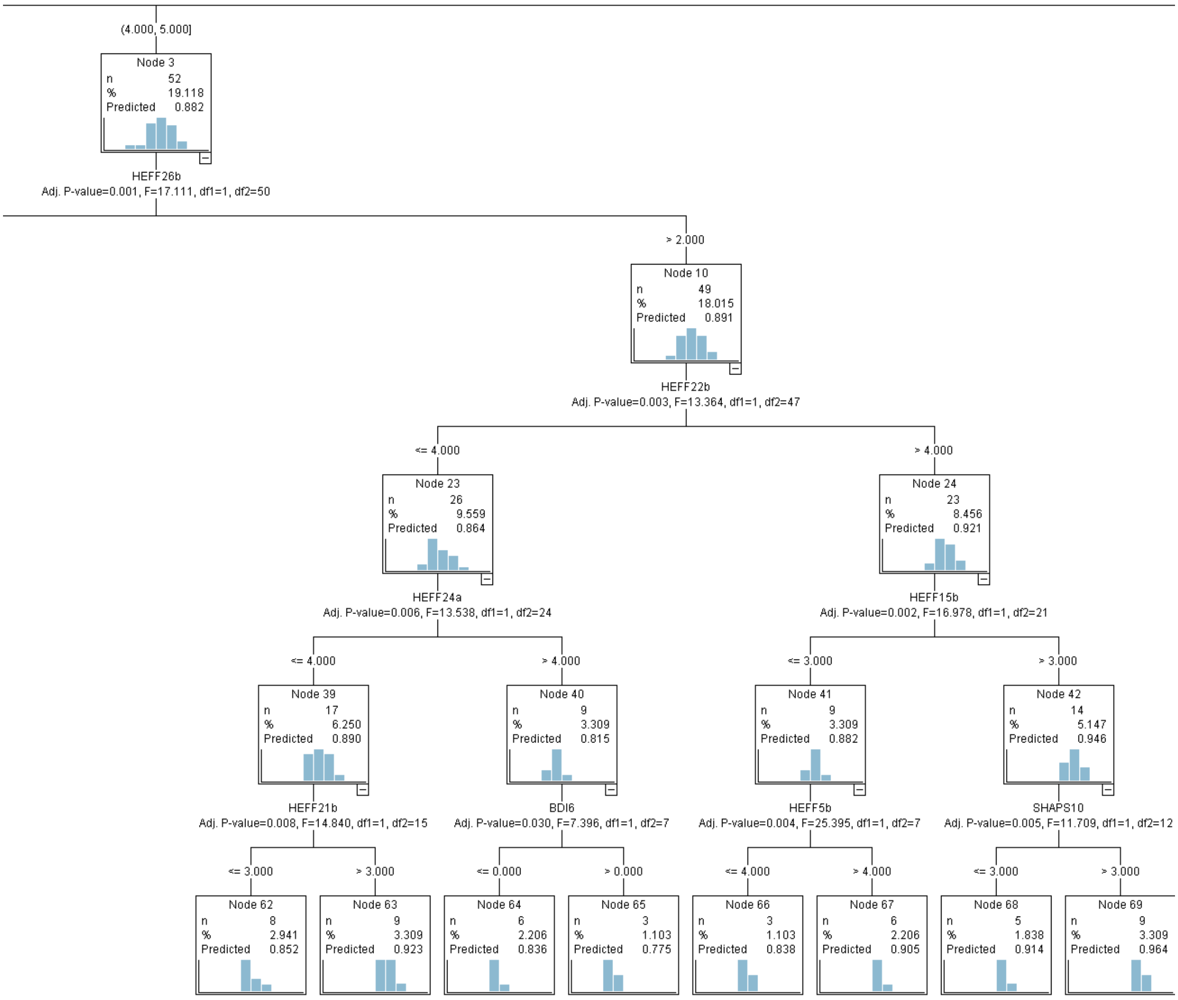

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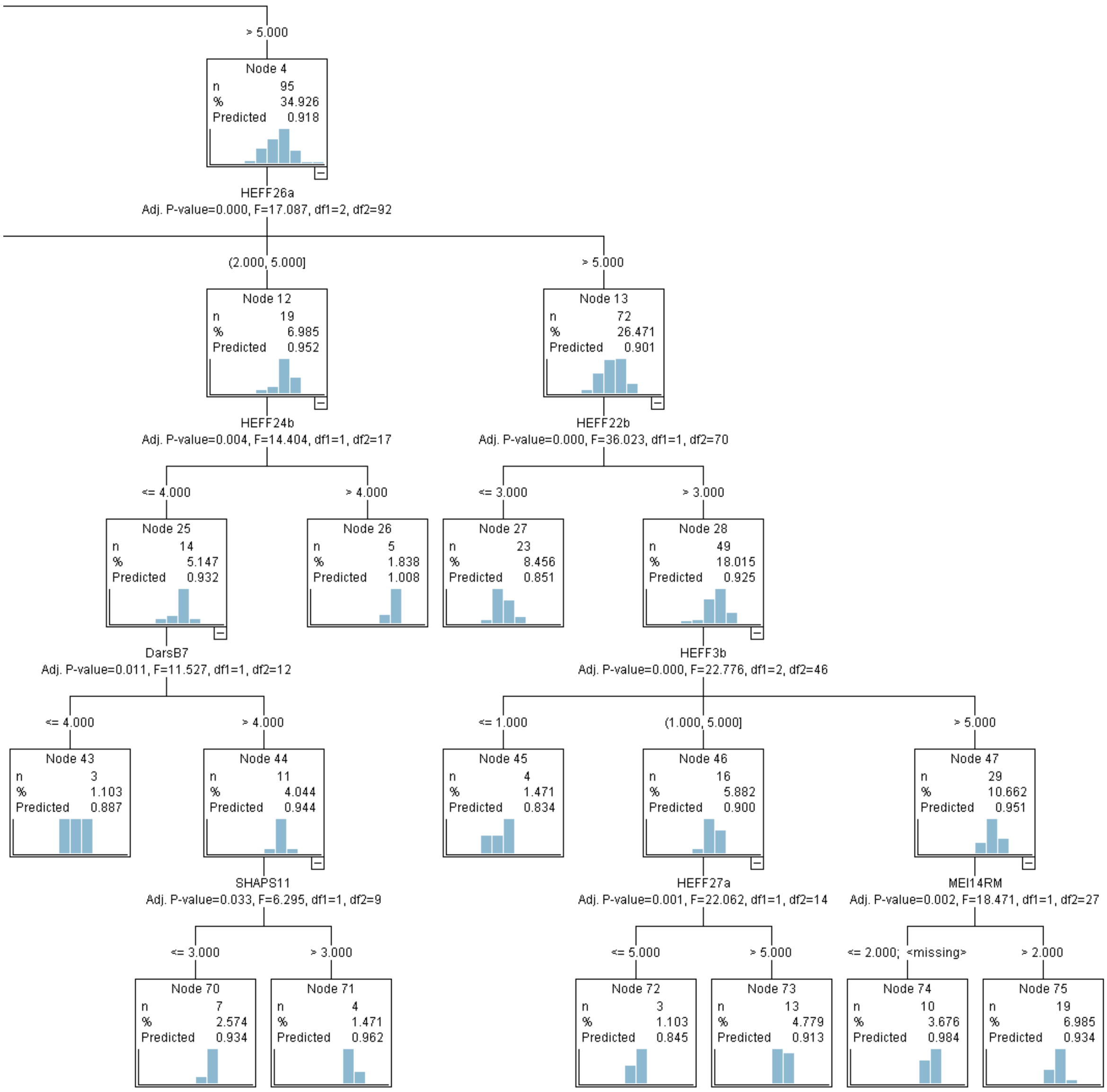


Figure 3.4 DT second iteration results of motivational-effort scale predictors from left to right.

3rd iteration

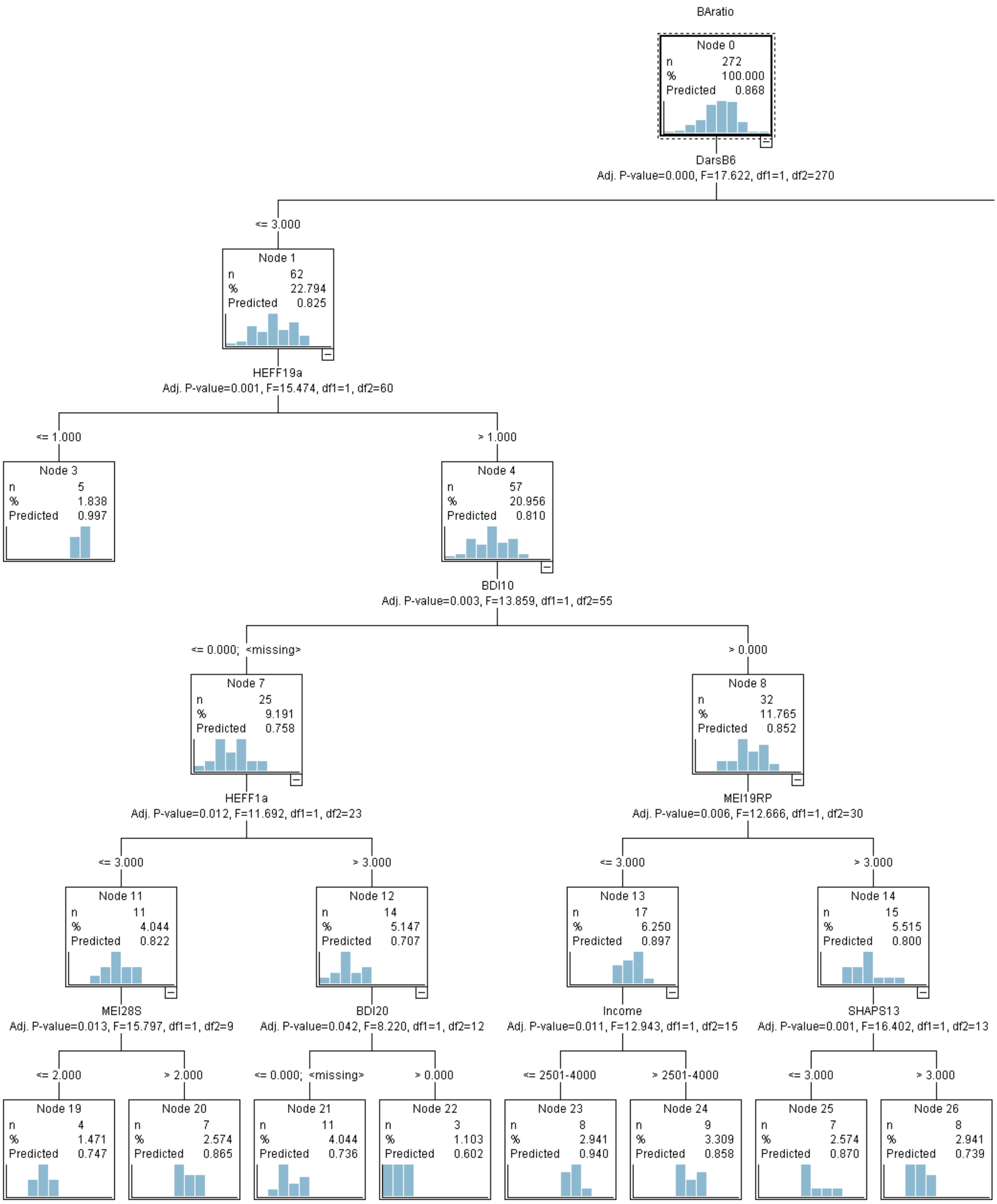
B items, age groups, and gender dominated the second iteration of the decision tree implementation, and were therefore removed in the 3rd iteration.

In the 3rd iteration, we found that the most significant predictor of the overall b/a score is item DARS B6 (make an effort to get/make favorite foods/drinks). In turn, DARS B6 splits the overall b/a score into 2 nodes in the second layer.

Participants who are less willing to get/make their favorite foods/drinks (DARS B6 <=3) were best predicted by item HEFFORT 19a (I like people). Those who do not like people (HEFFORT 19a <=1) had high motivation (b/a = 0.99), whereas those who like people (HEFFORT 19a >1) has somewhat lower motivation (b/a = 0.81) and were better predicted by BDI10 (crying).
Likewise, we found that participants who are more willing to get/make their favorite foods/drinks (DARS B6 >3) were predicted by HEFFORT 31a (I love to see people smile). Those more interested in seeing people smile (HEFFORT 31a >2) were better predicted by MEI 24 (amount of exercise, such as walking, swimming, or practicing yoga) and had moderately high motivation (b/a = 0.87). On the other hand, people less interested in people smiling (HEFFORT 31a <=2) had higher motivation (b/a = 0.99).

Seeing the primary nodes (HEFFORT 19a and 31a) we can link favorite food-related effort to feeling good around people. On the one hand, a lack of effort was linked to liking people and crying, a symptom of depression according to BDI, although others propose that crying is a symptom of anxiety [15]. In either case, less effortful people might like others for the comfort they provide. On the other hand, more effort to make or get favorite foods or drinks was linked to liking people smile and exercising. These items appear to have a social component in common. We can also see in the deeper nodes a link between depression symptoms (crying) and lack of motivation. This finding supports previous studies which found a link between depression and motivational deficits [16],[17]. We can also see that people more willing to exercise have higher motivation levels than others. This supports studies that link exercising to decreasing depression symptoms [18].

These observations indicate that a DARS item (B6), which measures motivation and pleasure related to making one's favorite foods/drinks was a better predictor of the overall b/a motivation score than HEFFORT's own (a) pleasure items or pleasure as measured by SHAPS, indicating that DARS B6 is not measuring pleasure per se. On the other hand, HEFFORT 19a and 31a, both involving others, were predictive of the DARS item, indicating a link between motivation and pleasure attained by socializing. Predictors and cut-off results are reported in DT Figures 3.5. from left to right.



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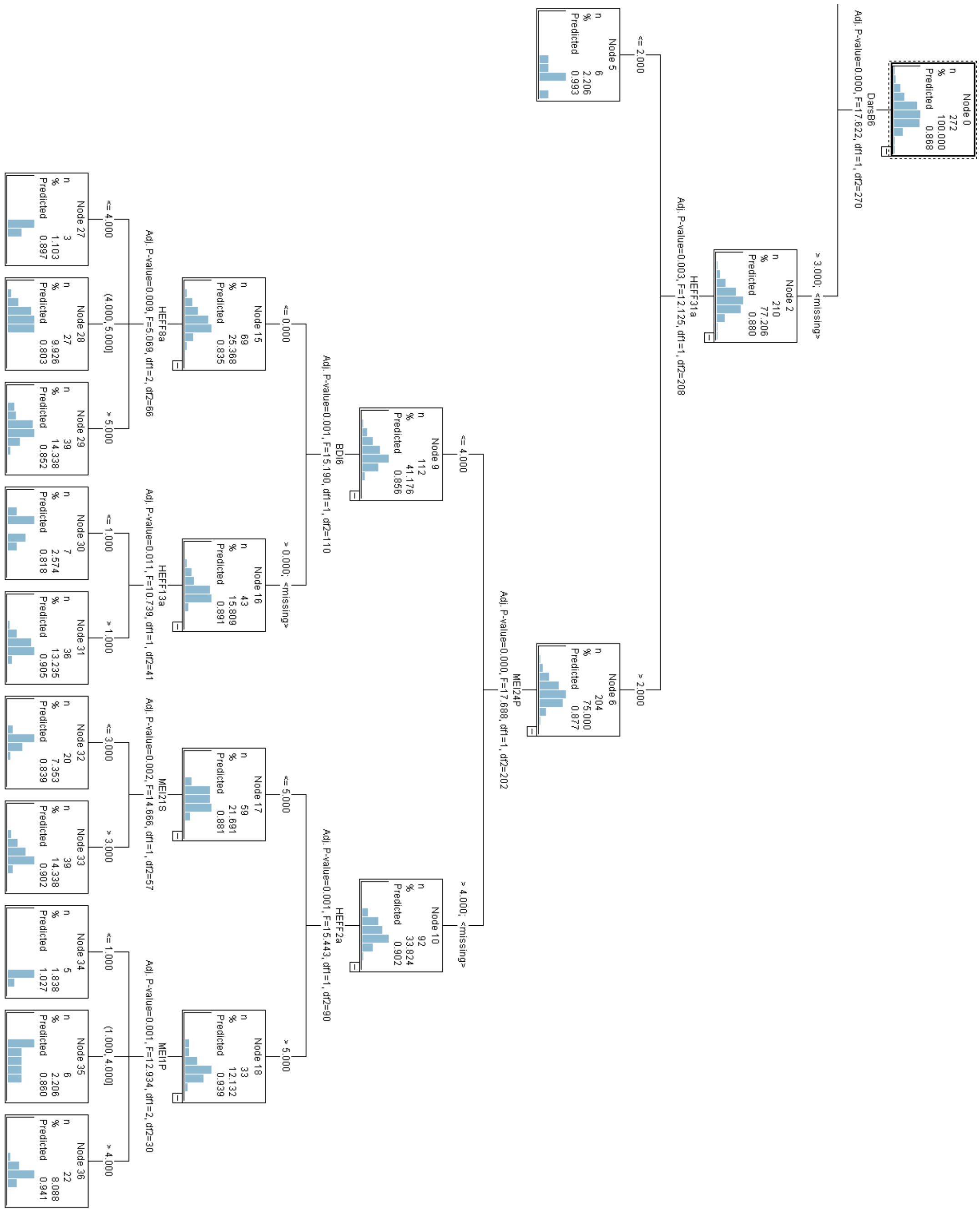


Figure 3.5 DT third iteration results of motivational-effort scale predictors from left to right.

4th iteration

In the 4th and last iteration, we removed all HEFFORT subscale items (a, b, and b/a), as well as previously significant predictors from other questionnaires. We found that the most significant predictor of the overall b/a score is item DARS D20 (make an effort to spend time having a sensory experience). In turn, DARS D20 splits the overall b/a score into 2 nodes in the second layer.

Participants less willing to spend time on a sensory experience (DARS D20 <=3) were best predicted by item MEI29 (interested in talking to others) and have moderately low motivation (b/a = 0.84). Participants less likely to talk to others (MEI29 <=1) were better predicted by DARS C11 (happy spending time doing social activities). Those happier in social activities (DARS C11 >4) had higher motivation (b/a = 0.89). Reciprocally, those more interested in talking to others (MEI29 >2) were better predicted by their interest in non-social hobbies/pastimes (DARS A4). Those not interested in such activities (DARS A4 <=1) had high motivation (b/a = 0.96) and were better predicted by SHAPS 4 (enjoy a favorite meal).

Likewise, we found that participants who are more willing to spend time on a sensory experience (DARS D20 >3) had moderately high motivation (b/a = 0.88) and were predicted by DARS C13 (planning social activities). Participants less willing to plan social activities (DARS C13 <=4) were better predicted by MEI22 (getting together with friends/family that don't live with you). On the fourth layer we can see that participants less interested in getting together with these friends/family (MEI22 <=3) had high motivation (b/a = 0.9) and were better predicted by DARS A1 (enjoying non-social hobbies/pastimes). Again, those who do not enjoy these activities (DARS A1 <=1) had high motivation (b/a = 1.05), and those who do enjoy such activities (DARS A1 >1) had slightly lower motivation (b/a = 0.89) and were predicted by BDI11 (feeling irritated) with most of them (n=34 out of 39) scoring low on this item. On the other hand, those more willing to plan social activities (DARS C13 >4) had moderately high motivation (b/a = 0.91) and were better predicted by MEI13 (prefer to be alone).

Participants who prefer to be alone (MEI13 >3) were better predicted by MEI3 (have trouble getting out of bed in the morning because you didn't want to face the day). Most participants (n=38 out of 44) in this layer scored <=5 on this item, and were better predicted by BDI8 (self-blame).

Third layer nodes display a contradiction with the second layer, suggesting that people preferring to be alone or doing non-social activities (introverts) have higher motivation to talk to others and plan events. While those who spend time in social activities and get together with friends (extroverts) were less motivated to talk to others and plan social events.

These results suggest that people who enjoy their own company but participate in social events are more motivated than those who prefer the company of others. This may be due to the effort required to plan and actively participate in social events, in contrast to simply being around friends and having them do the planning or talking.

These observations suggest that DARS and MEI, which measure motivation, energy and pleasure, have items which are successful predictors of the overall b/a motivation score, specifically effortful items on the sensory and social scales. On the other hand, SHAPS and BDI, which measure pleasure and aspects of depression, respectively, do not predict effortful motivation, as reflected by the overall b/a score in HEFFORT, very well. Thus, we conclude from all iterations that b/a is a measure of effortful motivation and not pleasure. Predictor items and cut-off results are reported in the DT Figure 3.6.

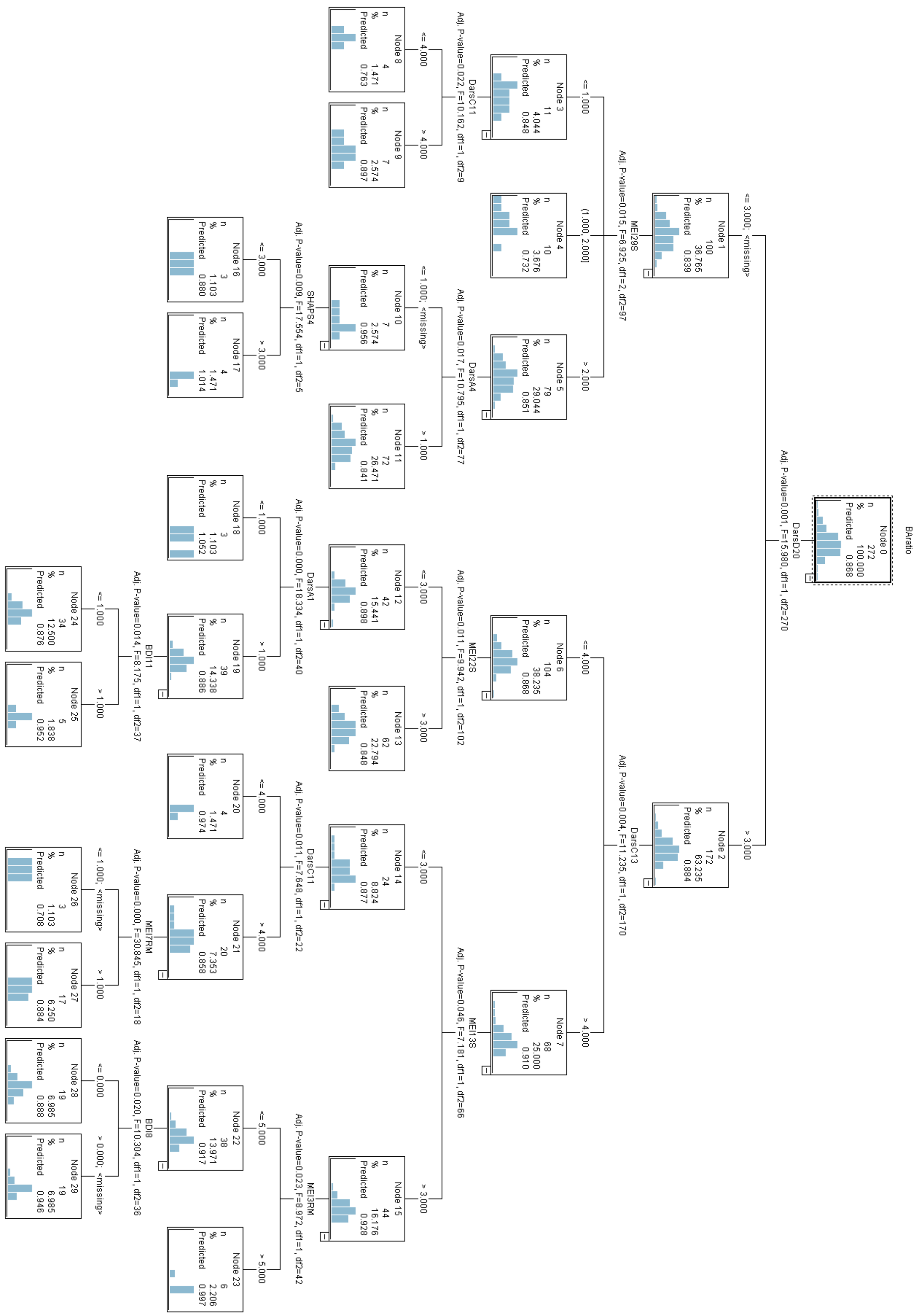


Figure 3.6 DT 4th iteration results of motivational-effort scale predictors.

3.6.2 Decision trees results of HEFFORT b/a items

The main aim of this study is to measure effortful-motivation separate from pleasure. We hypothesize that the b/a ratio on HEFFORT is a pure effort measure. Therefore, we implemented our decision tree algorithm on HEFFORT's b/a items to investigate which of the individual b/a items significantly predict the overall b/a motivational score.

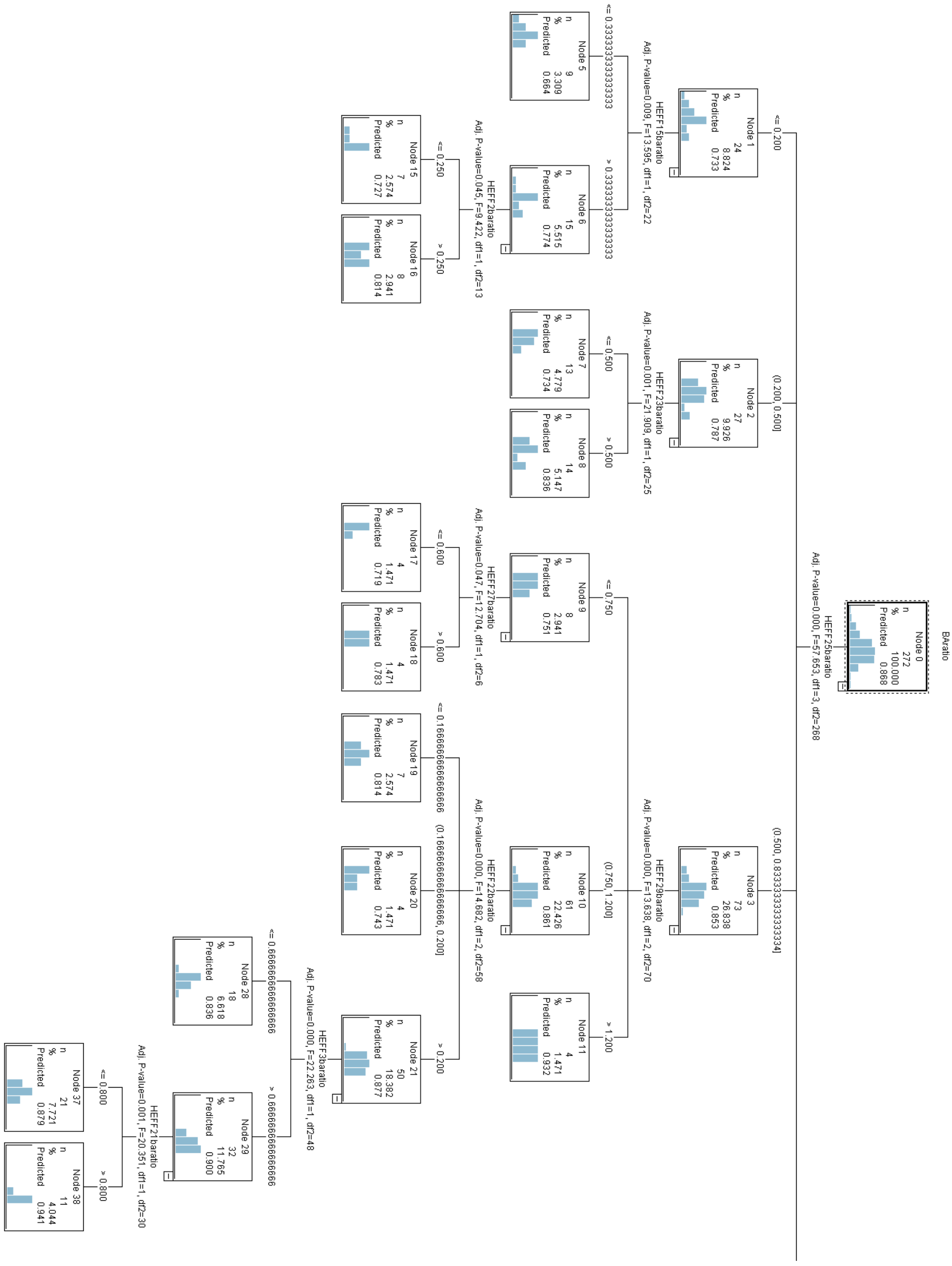
We found that the most significant predictor of the overall b/a score was item HEFFORT 25b/a (making home-cooked food). In turn, HEFFORT 25b/a split the overall b/a score into 4 nodes in the second layer.

Participants with the least motivation to prepare home-cooked food (HEFFORT 25b/a <=0.2) had moderately low motivation (b/a = 0.73) and were best predicted by item HEFFORT 15b/a (dog training). Those who were willing to train dogs (HEFFORT 15b/a > 0.3) were predicted by HEFFORT 2b/a (making new food), both implying surprise and novelty.

Furthermore, participants with moderate motivation to prepare home-cooked food (0.2< HEFFORT b/a25 < 0.5) also had moderately low motivation (b/a - 0.78) and were better predicted by HEFFORT 23b/a (preparing smoothies/fruit salad), which was linked to DARS energy item when all questionnaires were included.

Participants with higher motivation to make home-cooked food (0.5 < HEFFORT b/a25 <0.83) had slightly higher motivation (b/a = 0.85) and were better predicted by HEFFORT 29b/a (doing sport), clearly indicating that people with higher motivation are more likely to exert effort on social-physical activities. Those less willing to do sports (HEFFORT 29b/a <=0.75) were distinguished by their willingness to wake up early and watch the sunrise (HEFFORT 27b/a) but had lower motivation (b/a = 0.75). On the other hand, those with higher motivation to do sports (0.75< HEFFORT 29b/a <1.2) were better predicted by HEFFORT 22b/a (taking cooking classes) and had higher motivation (b/a = 0.86), indicating that social/self-care experiences require more effort. Additionally, participants with the highest motivation to do sports (HEFFORT 29b/a >1.2) had the highest motivation (b/a = 0.93). Thus, we can link high motivation to physical activity.

As for participants with the highest motivation to make home-cooked food (HEFFORT b/a25 >=0.83), we found the same results as in the first iteration when we entered all questionnaires items, which were b/a effortful items, including taking cooking classes, enjoying home cooked food, waking up to see the sunrise and spending time under the sun, being linked to high and moderately high motivation (b/a = 0.95) Predictors and cut-off results are reported in Figure 3.7. from left to right.



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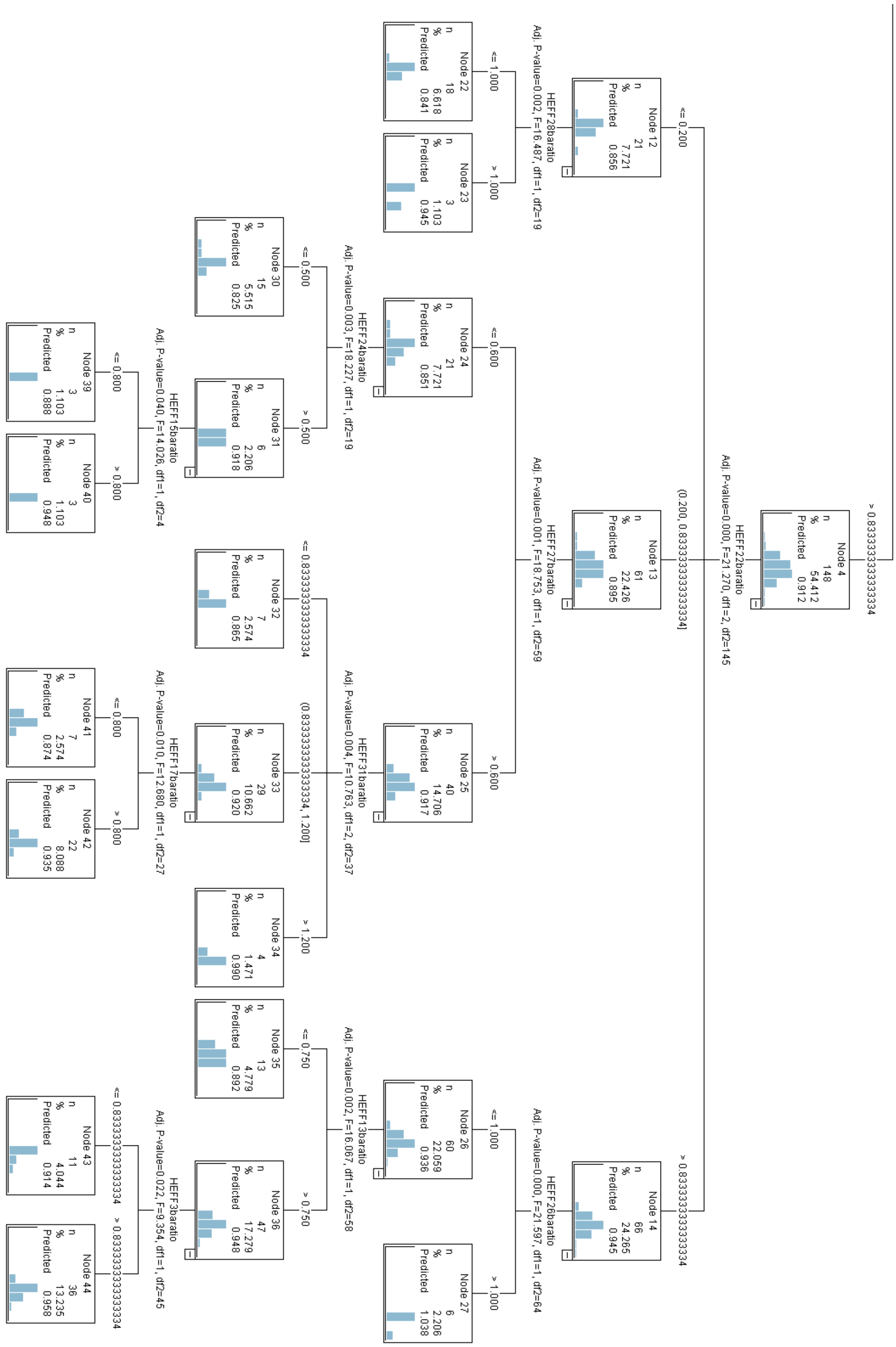

Figure 3.7 DT results of b/a items predicting motivational-effort scale from left to right.

3.6.3 Decision trees results of HEFFORT b items

In an effort to further explore HEFFORT, we implemented DT algorithm on b items representing the compound of both pleasure and effort needed to achieve it.

In this iteration, the most significant predictor of the overall b/a score is item HEFFORT 25b (making home-cooked food). It splits the overall b/a score into 4 nodes in the second layer.

Participants with low motivation to prepare home-cooked food (HEFFORT b25 $<=1$) had moderately low motivation (b/a = 0.75).

Participants with moderate motivation to prepare home-cooked food ($1<$ HEFFORT b25 < 4) had slightly higher motivation (b/a = 0.85) and were better predicted by HEFFORT 29b (doing sports), confirming all past analyses that physical energy is linked to moderate motivation. Participants more willing to do sports (HEFFORT 29b >3) had higher motivation (b/a = 0.87) than those who are not (b/a =0.76). They were also better predicted by HEFFORT 2b (making new food).

Participants with the highest motivation score (HEFFORT 4 $<=$ b25 >5) were distinguished by their willingness to take cooking classes (HEFFORT 22b) and their high motivation (predicted b/a) scores. Participants more motivated to take cooking classes (HEFFORT 22b >4) have higher b/a score (b/a = 0.94) and are more willing to make bread by themselves. In the last two analyses using b/a and b items as input, respectively, we found that higher motivation is linked to social/self-care experiences like taking cooking classes, whereas lower and moderate motivation is more linked to novelty and internal hedonic experiences like making new foods, and spending time under the sun.
Predictors and cut-off results are reported in Figure 3.8.

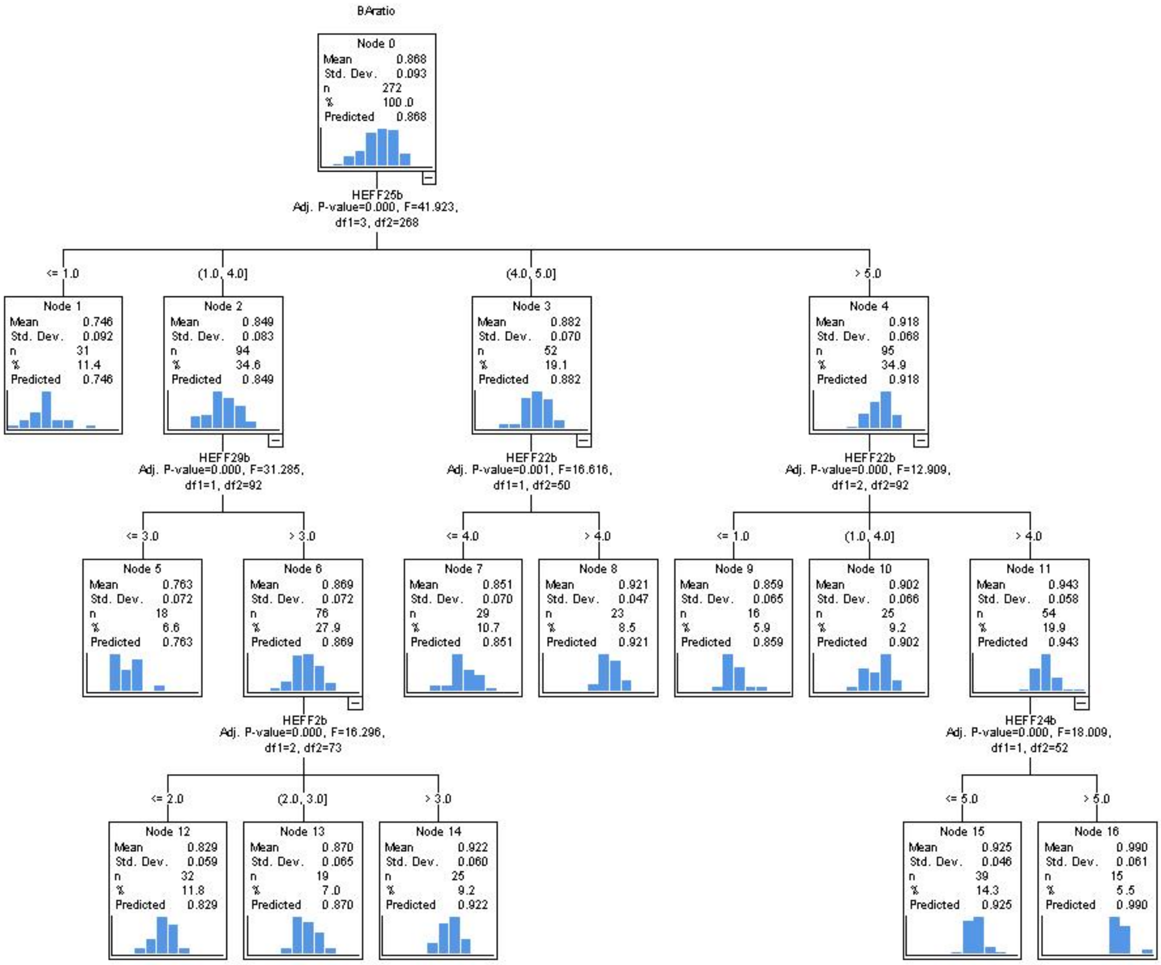

Figure 3.8 DT results of b items predicting motivational-effort scale.

3.6.4 Decision trees results of HEFFORT a items

To explore HEFFORT's pleasure (a) items, we used the (a) items as input to our decision tree algorithm and obtained 4 items only. Removing effortful items from the HEFFORT scales, we found that the most significant predictor of the overall b/a score was item HEFFORT 14a (I love nature) which splits b/a into 2 nodes.

Participants who are not very interested in nature (HEFFORT 14a <=2) comprise only 1.83% (n=5) of the whole sample, with higher predicted motivation level (b/a = 1.027). The rest of the participants were split by HEFFORT 2a (I love tasting new foods) with moderately low motivation level (b/a = 0.865).

Participants with low and moderate liking to taste new foods (HEFFORT 2a $<=$5) had moderately low motivation (b/a = 0.85) and were better predicted by HEFFORT 31a (I love to see people smile), while those with the highest liking to taste new food (HEFFORT 2a $>$5) had moderately high motivation (b/a = 0.89) and were better predicted by HEFFORT 26a (I love the sun).
Additionally, participants who do not love the sun (HEFFORT 26a $<=$ 1) had high motivation (b/a = 1.02).

This iteration's results suggest that when no effort is exerted (no effort items included) effortful motivation is better predicted by items which reflect positive sensations like experiencing nature, seeing smiles on people,and tasting new foods, which can involve other people. This indicates that individuals who are more and less effortful take pleasure in sensory experiences, but have different preferences.
Predictors and cut-off results are reported in Figure 3.9.

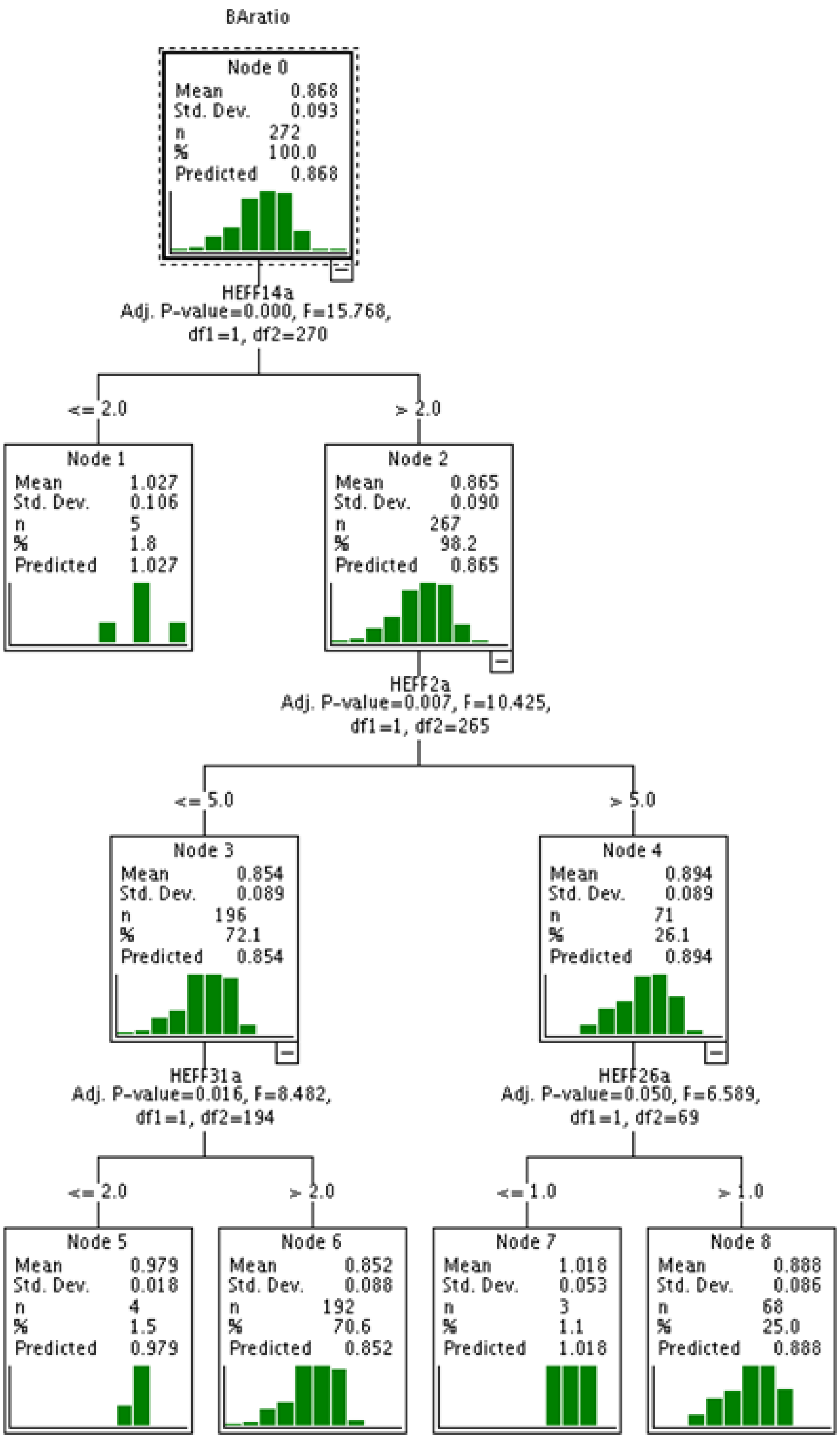

Figure 3.9 DT results of a items predicting motivational-effort scale.

3.6.5 Previously validated questionnaires' items as input to decision tree algorithm

To ensure the validity of HEFFORT as a psychiatric tool to measure pleasure and effortful motivation, and to explore similarities to previously validated questionnaires, we used MEI, DARS, SHAPS and BDI items as input to our decision tree algorithm to predict HEFFORT's overall b/a score.

MEI

Entering MEI items to predict the overall b/a score, we found the most significant predictor to be item MEI 19 (feeling energetic) indicating a link between motivation and physical energy.
Contrastingly, participants who do not feel energetic (MEI 19 $<=$1) had moderately high motivation in this case (b/a $=$ 0.92).
In turn, participants feeling energetic (MEI 19 $>$ 1) had moderately low motivation (b/a $=$ 0.86) and were predicted by MEI 24 (exercise). With those who moderately exercise (MEI 24 $<=$3) were better predicted by MEI 3 (have trouble getting out of bed in the morning because you didn't want to face the day) with the majority of participants (n=93) having lower scores on this item (MEI 3 $<=$5). The more difficult it is to get out of bed (MEI 3 $>$ 5) the lower the motivation (b/a $=$ 0.75).
These results indicate that MEI physical energy items are linked to moderately low motivation. Unlike HEFFORT physical activity items which link to higher motivation. This may be because HEFFORT physical activity items are a combination of physical and social activities. Thus, the reason for higher motivation may be the people factor more than the physical activity itself. Predictors and cut-off results are reported in Figure 3.10.

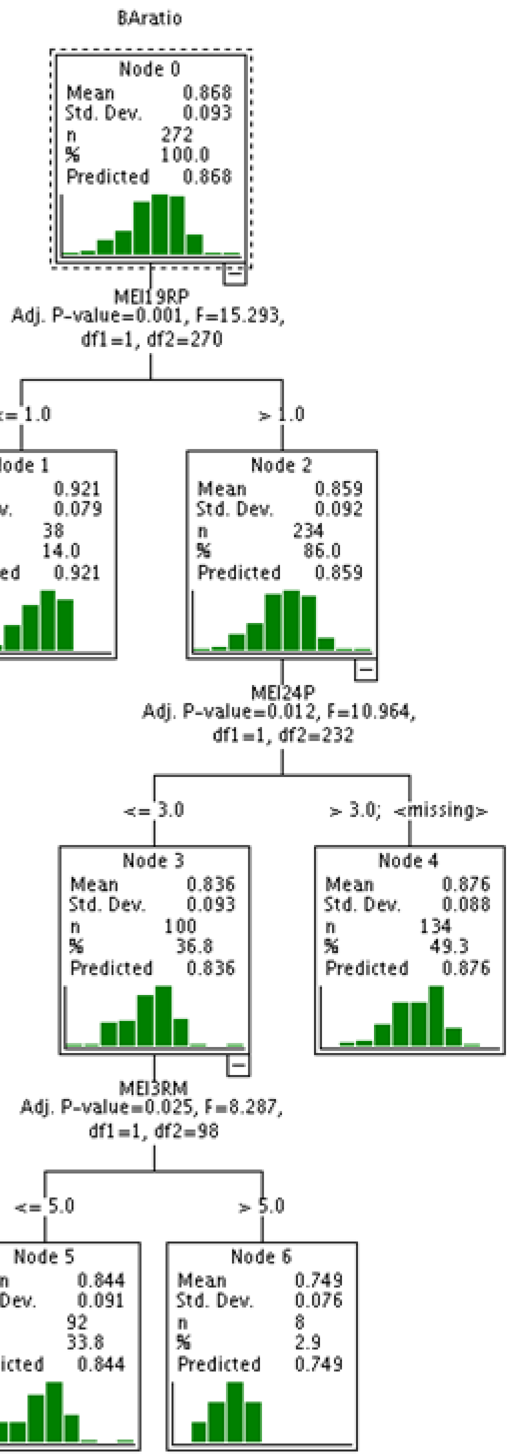

Figure 3.10 DT results of MEI items predicting motivational-effort scale.

DARS

The most significant predictor of the overall b/a motivation score is item DARS B6 (make an effort to get/make these foods/drinks). In turn, DARS B6 splits the b/a score into 2 nodes.

Participants less willing to make an effort to get foods/drinks (DARS B6 <=3) had moderately low motivation (b/a = 0.83) and were better predicted by DARS D20 (make an effort to spend time having a sensory experience). Those less willing to make an effort to spend time on a sensory experience (DARS D20 <=3) had lower motivation scores (b/a = 0.79) and were better predicted by DARS C12 (social activities and doing things involving other people), while participants willing to make an effort to spend time on a sensory experience (DARS D20 <=3) were better predicted by DARS A2 (spending time doing a hobby that doesn't involve people). These results indicate that less effortful individuals can be divided into those that find pleasure in sensory experiences alone, and others who prefer engaging in social activities with others.

On the other hand, participants more willing to make foods/drinks (DARS B6 >3) had moderately high motivation (b/a = 0.88) and were better predicted by DARS C13 (planning social events). This supports our previous results in the 3rd DT, where we found a link between food-related motivation and social motivation. Predictors and cut-off results are reported in Figure 3.11.

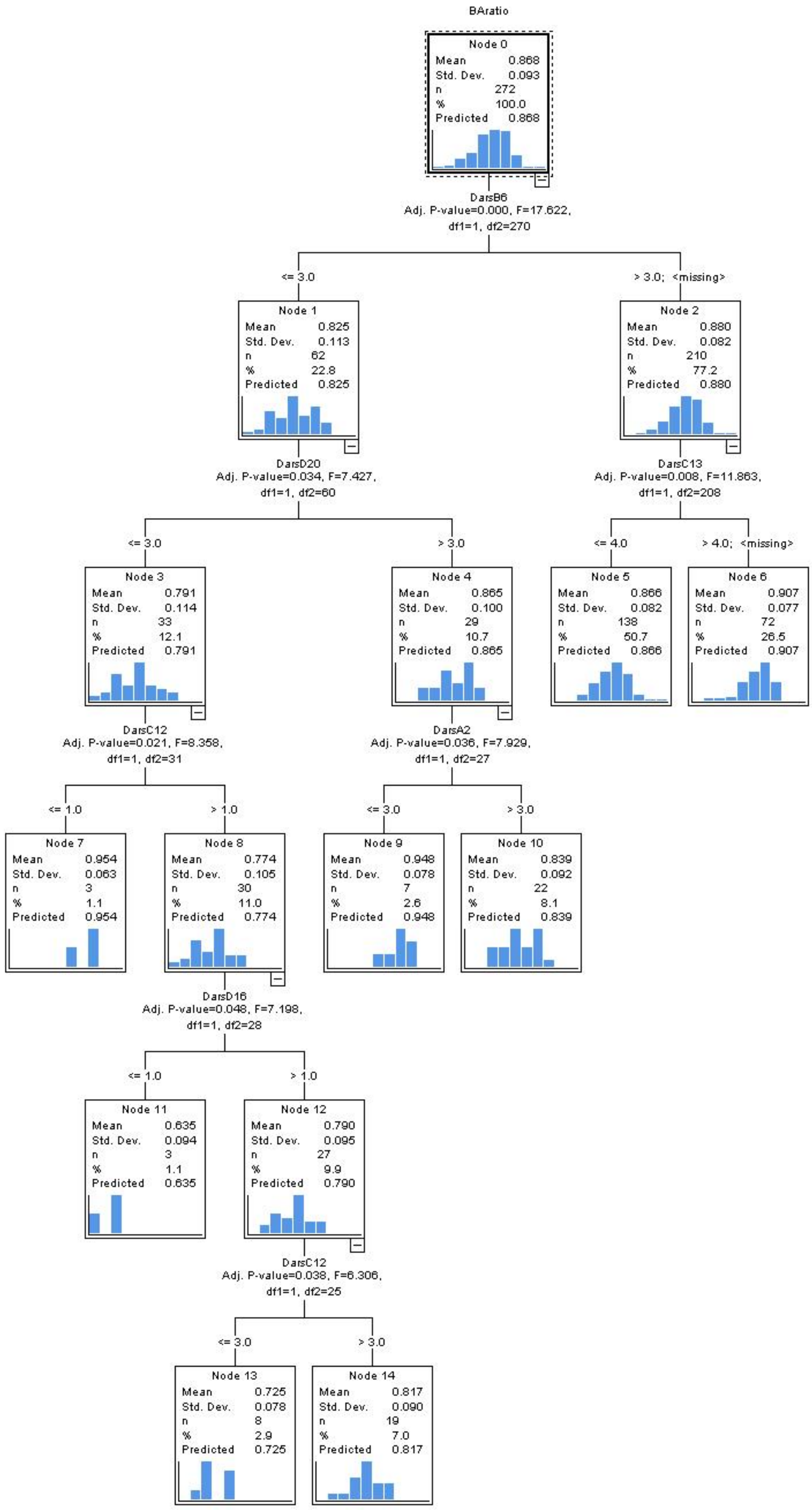

Figure 3.11 DT results of DARS items predicting motivational-effort scale.

SHAPS

SHAPS aims to measure hedonic or pleasure capacity. Therefore, we speculate that SHAPS items should not contribute to the b/a effortful-motivation score. Nonetheless, using SHAPS items as input to our DT algorithm we obtained a single item SHAPS 1 (I would enjoy my favorite television or radio program) as a significant predictor of our overall b/a score. We have also observed that lower results on this item (SHAPS 1$<$1) reflected a higher b/a motivation score (b/a $=$ 0.912), whereas for (SHAPS $>$1) we found lower motivation scores (b/a $=$ 0.863).

Repeating the splitting with removing this item did not result in other independent variables. Thus, confirming our speculation that SHAPS, as a pleasure measurement tool, should not have a significant effect on a motivation measurement scale. Predictors and cut-off results are reported in Figure 3.12.

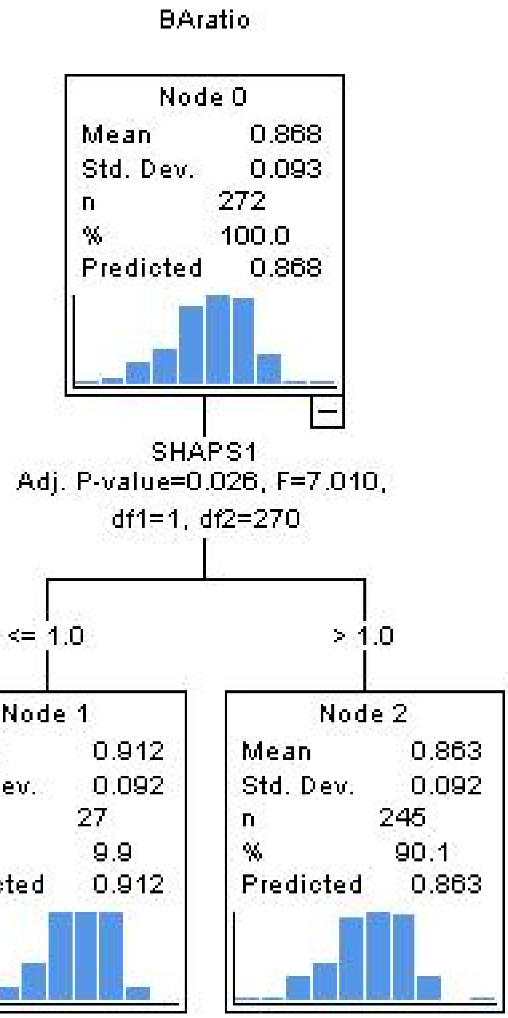

Figure 3.12 DT results of SHAPS items predicting motivational-effort scale.

BDI

BDI is a tool used to evaluate depression severity. However, none of the items appear to measure motivation level, although depression is usually associated with motivational deficiency [19]. Thus, we speculated that BDI items do not predict the overall b/a score on HEFFORT, measuring effortful-motivation. The data extracted from implementing DT algorithms on BDI items supports our hypothesis. We observed no independent contributions to the overall b/a score.

3.6.6 Multiple Linear Regression

We applied multiple linear regression (MLR) to assign each feature (demographics and items in questionnaires) a certain weight, this weight quantifies the importance of this feature in predicting the final b/a score.

Demographics

The only demographical variable statistically significant to the final b/a score is income (beta=-0.142, $p<0.05$). As for the other demographics (age, gender, education level, medicine use), p values do not exceed the 0.05 threshold to reject the null hypothesis, therefore, do not reliably predict the motivation score. Results are reported in Table 3.19.

All Questionnaires' Items

We have included all items in the multiple linear regression analysis. On the other hand, we have ignored incomplete data (NaN) during regression for more accurate results, this lead to 272 valid HEFFORT scores (B/A) for evaluation The mean for

Table 3.19
Motivation scale b/a ratio's MLR results of demographical variables.

	U Coef. B	U Coef. Std. Error	St. Coef Beta	St. Coef t	St. Coef Sig.
(Constant)	0.888	0.053		16.88	0
AgeGroup	-0.004	0.004	-0.065	-0.93	0.353
Gender	0.012	0.012	0.065	1.011	0.313
Education	-8.41E-05	0.008	-0.001	-0.011	0.991
Income	-0.011	0.005	-0.142	-2.056	0.041
Medicine	0.004	0.021	0.014	0.209	0.834

Dependent Variable b/a

U Coef: Unstandardized Coefficients

St. Coef: Standardized Coefficients

the final B/A score is 0.867 ± 0.092, with the pleasure (a) items total score mean 144.06 ± 16.78, and the effort + pleasure compound total score mean 125.63 ± 19.14. A total of 162 questionnaires' items resulted in 46 statistically significant items as predictors of the motivation level (b/a score). Of which, 10 (21.74%) were social/self-care experience items, 8 (17.39%) smell/taste items, 6 (13.04%) hygiene and self-care items, 6 (13.04%) novelty items, 5 (10.86%) feel good items, 4 (8.69%) home items, 3 (6.53%) social-physical items, 2 (4.34%) social activity items, 1 (2.17%) mental item, and 1 (2.17%) physical item.

Results were dominated by social/self-care experiences and smell/taste items as predictors of the overall b/a motivation level. Consistent with the decision tree algorithm results, income (beta=-0.142, $p<0.05$) was the only demographical variable significant to the b/a ratio, and a dominance of social/self-care items followed by smell/taste items was observed. Statistically significant items to the motivation level (b/a scale) are reported in Table 3.20. Note item categories are:
H-Sc: Hygiene and Self-care, F: food (smell/taste), FG: feel good, H: home, S-Sc: social/self-care experience, M: mental, N: novelty/surprise, Ph: physical activity, Soc: social activity, S-Ph: social-physical item.

Table 3.20
Motivation scale b/a ratio's MLR results of all questionnaires' items.

	Category	U. Coef. B	U. Coef. Std. Error	St. Coef. Beta	St. Coef. t	St. Coef. Sig.
(Constant)		0.812	0.069		11.684	0
SHAPS4	F	-0.005	0.002	-0.027	-2.166	0.035
HEFF1a	F	-0.012	0.002	-0.192	-7.451	0
HEFF1b	F	0.014	0.002	0.24	6.535	0
HEFF2b	N	0.006	0.001	0.105	4.014	0
HEFF6b	H-Sc	0.007	0.003	0.092	2.081	0.042
HEFF7a	S-Sc	-0.022	0.008	-0.181	-2.807	0.007
HEFF7b	S-Sc	0.026	0.008	0.334	3.157	0.003
HEFF8b	H-Sc	0.006	0.002	0.071	3.427	0.001
HEFF10a	H-Sc	-0.004	0.001	-0.058	-2.827	0.007
HEFF10b	H-Sc	0.005	0.001	0.082	4.37	0
HEFF11a	H	-0.008	0.002	-0.102	-3.297	0.002
HEFF11b	H	0.009	0.002	0.129	4.481	0
HEFF12a	FG	-0.006	0.002	-0.083	-2.814	0.007
HEFF13a	S-Ph	-0.005	0.002	-0.099	-2.612	0.012
HEFF13b	S-Ph	0.007	0.002	0.126	3.033	0.004
HEFF14a	N	-0.011	0.004	-0.112	-3.117	0.003
HEFF14b	N	0.014	0.003	0.143	3.924	0
HEFF15b	N	0.006	0.002	0.126	2.563	0.013
HEFF17a	H	-0.005	0.002	-0.061	-2.292	0.026
HEFF17b	H	0.008	0.001	0.131	6.566	0
HEFF19b	FG	0.008	0.002	0.111	3.991	0
HEFF22a	S-Sc	-0.007	0.003	-0.067	-2.376	0.021

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	Category	U. Coef. B	U. Coef. Std. Error	St. Coef. Beta	St. Coef. t	St. Coef. Sig.
HEFF23a	S-Sc	-0.006	0.002	-0.066	-2.506	0.015
HEFF23b	S-Sc	0.006	0.002	0.109	2.742	0.008
HEFF24a	F	-0.006	0.001	-0.104	-4.81	0
HEFF24b	F	0.008	0.002	0.135	4.472	0
HEFF25a	S-Sc	-0.008	0.004	-0.088	-2.324	0.024
HEFF25b	S-Sc	0.009	0.004	0.16	2.321	0.024
HEFF31a	FG	-0.01	0.003	-0.113	-4.055	0
HEFF31b	FG	0.01	0.002	0.103	5.105	0
MEI4RP	Ph	0.003	0.002	0.061	2.242	0.029
MEI7RM	M	0.003	0.001	0.055	2.354	0.022
MEI11RS	Soc	0.003	0.001	0.058	2.363	0.022
MEI28S	Soc	0.004	0.002	0.058	2.15	0.036
BDI18	F	0.004	0.002	0.028	2.576	0.013
HEFF1baratio	F	-0.029	0.008	-0.095	-3.679	0.001
HEFF2baratio	N	0.012	0.006	0.055	2.064	0.044
HEFF5baratio	S-Sc	0.04	0.014	0.127	2.797	0.007
HEFF7baratio	S-Sc	-0.096	0.044	-0.171	-2.184	0.033
HEFF10baratio	H-Sc	0.008	0.004	0.048	2.046	0.046
HEFF14baratio	N	-0.038	0.016	-0.108	-2.369	0.021
HEFF16baratio	F	0.037	0.013	0.134	2.808	0.007
HEFF26baratio	S-Sc	0.026	0.013	0.079	2.045	0.046
HEFF28baratio	S-Ph	0.018	0.006	0.087	3.116	0.003
HEFF31baratio	FG	-0.016	0.007	-0.08	-2.294	0.026
HEFF33baratio	Ap	0.024	0.008	0.096	2.923	0.005

Dependent Variable: b/a

U Coef: Unstandardized Coefficients

St. Coef: Standardized Coefficients

3.6.7 Multiple Linear Regression Results as Input to The DT Algorithm

For the sake of dimensionality reduction, we used our multiple linear regression (MLR) results as input to our DT algorithm.
In this iteration we entered the results of the multiple linear regression (MLR) as input to the decision tree algorithm.

We found the most significant predictor of the overall motivation b/a score to be item HEFFORT 16b/a (cooking). In turn, item HEFFORT 16b/a split the overall b/a score into 4 nodes.
Participants with almost no motivation to cook (HEFFORT 16b/a <=0.166) had the lowest motivation (b/a = 0.7) and were better predicted by item MEI4 (run out of energy before the end of the day).
Higher score on this item (MEI 4 > 3) links to very low motivation (b/a = 0.62). In turn, those who do not run out of energy very often (MEI4 <=3) were predicted to have slightly higher motivation scores (b/a =0.732). Deeper into the third layer we found that people with better energy levels (MEI4 <=3) were better predicted by item HEFFORT 14b (I love walking/hiking in nature). This result indicates a link between physical energy and novelty items.

On the other hand, participants with moderate motivation to cook (0.166 < HEFFORT 16b/a <=0.5) had moderately low motivation (b/a = 0.78) and were better predicted by HEFFORT 6b (make time to meet with friends). Participants who do not make time to meet with friends (HEFFORT 6b <=3) had slightly higher motivation (b/a = 0.86) than participants who meet friends.
Participants who moderately enjoy meeting with friends (3< HEFFORT 6b <5) had lower motivation (b/a = 0.75) and were better predicted by MEI7 (procrastinate or put things off until another day) with the majority (n = 18/22) scoring less than 4, indicating a link between physical energy and items reflecting self-care and appeal to others, according to our previous factor analysis results.

Likewise, people who highly enjoy meeting up with friends (HEFFORT 6b>5) had slightly higher motivation (b/a = 0.84) and were better predicted by HEFFORT 11b (I love entertaining/socializing in my home). This result suggests a link between home and socializing.

Participants with higher motivation to cook (5< HEFFORT 16b/a <=0.8) had slightly higher motivation (b/a = 0.85) and were better predicted by a novelty item HEFFORT 2b (I make new foods). Participants who enjoy making new foods (HEFFORT 2b >1) had higher motivation (b/a = 0.87) in comparison to those who do not enjoy new foods who scored lower (b/a = 0.77). Also, participants who have higher motivation (b/a = 0.87) were better predicted by HEFFORT 10b (I work out to have a fit body) a hygiene and self-care item.

Participants with the highest motivation to cook (HEFFORT 16b/a >0.8) had moderately high motivation (b/a = 0.9) and were better predicted by HEFFORT 7b/a (make time to be by the seaside). An social/self-care experience item. The higher the score on this item, the higher the motivation.

Those with low motivation to make time for being on the seaside (HEFFORT 7b/a <=0.5) had moderately low low motivation (b/a = 0.76).
Those with moderate motivation to make time to be on the seaside (5< HEFFORT 7b/a <=0.833) had moderately high motivation (b/a = 0.87) and were better predicted by HEFFORT 12a (I love people) with most of them (n=20/33) scoring high on HEFFORT 12a. Again, participants who love people (HEFFORT 12a >4) were better predicted by HEFFORT 26b/a (spending time under the sun) an social/self-care experience. This branch indicates a link between social/self-care experiences and higher motivation scores.
Nonetheless, participants who love people less (HEFFORT 12a <=4) had higher motivation (b/a = 0.91) compared to those who love people more (b/a = 0.84).

In the last branch with the highest predicted motivation level (b/a = 0.92), we found participants with the highest motivation to cook to be better predicted by a food item HEFFORT 24b (I would make bread myself).

Most participants (n=114/136) had a moderate score on this item (HEFFORT 24b <=5) and had slightly lower motivation (b/a = 0.91) than the rest. They were also predicted by HEFFORT 15b (I love to train dogs). Those who don't necessarily enjoy training dogs (HEFFORT 15b <=3) were better predicted by HEFFORT 10b (I work out to have a fit body), whereas those who enjoy training dogs (HEFFORT 15b >3) had higher motivation (b/a = 0.93) and were predicted by HEFFORT 2b/a (make new foods), both novelty items.

On the other hand, participants who very much enjoy making bread (HEFFORT 24b >5) had the highest motivation (b/a = 0.97) and were better predicted by HEFFORT 14a (I love nature) a novelty item. The majority (n=19/22) love nature (HEFFORT 14a >2) and are better predicted by another novelty item HEFFORT 2b (I make new foods). Thus, linking novelty to higher motivation.

The results of this iteration indicate, firstly, that HEFFORT's items are better predictors of the overall b/a score. This is clear by the dominance of b/a and b items in the branches.
Second, novelty-related effortful items are successful predictors of higher motivation. Predictors and cut-off results are reported in Figure 3.13. from left to right.

3.7 Predictors of Motivation Levels

Based on our mathematical model and the clusters we found in the k-means analysis, we categorized motivation levels (overall b/a scores) into 4 categories, low, moderate low, moderate high, and high.
Low motivated participants were more likely to be predicted by HEFFORT's novelty items (n=4/9 items).
Moderately low motivated participants' predictors were dominated by food (n=3), and social (n=3) items, followed by hobbies. We can also see that HEFFORT items (n=7) are dominant followed by DARS items (n=5).
Moderately high motivated people were better predicted by HEFFORT social/self-care

items (n=5).

Highly motivated participants' predictors were mostly dominated by social/self-care experience items (n=7/10).

The most significant predictors of each motivation level and their categories is reported in Table 3.21. and Figures 3.14. - 3.17.

Table 3.21

Significant predictors of each motivation level.

Low	Type	Low mod.	Type	High mod.	Type	High	Type
HEff8a	H-Sc	HeffF6b	H-Sc	Heff10b	H-Sc	Heff24b	F
Heff1a	F	BDI10	Crying	Heff31a	FG	Heff22b/a	S-Sc
MEI6	M	Heff16b	F	Heff1b	FG	Heff26a	S-Sc
Heff15b	N	Heff24a	F	Heff16b	FG	Heff7b/a	S-Sc
Heff15b	N	SHAPS4	F	DARS A1	Hobbies	Heff25b/a	S-Sc
Heff15b/a	N	Heff19a	FG	Heff22b	S-Sc	Heff26b/a	S-Sc
Heff2b/a	N	DARS A2	Hobbies	Heff22b/a	S-Sc	Heff27b/a	S-Sc
MEI4	Ph	DARS A4	Hobbies	Heff27b/a	S-Sc	MEI19	Ph
Heff28b	S-Ph	Heff23b/a	S-Sc	Heff29b/a	S-Sc		
		Heff29b	S-Sc	Heff26b/a	S-Sc		
		MEI7	M	BDI11	Irritation		
		Heff2b	N	Heff2b	N		
		MEI19	Ph	MEI24	Ph		
		DARS20	S	DARS14	Soc		
		DARS C11	Soc	SHAPS1	Soc		
		DARS C12	Soc	DARS C13	Soc		
		MEI29	Soc	MEI22	Soc		

Items categories: H-Sc: Hygiene and Self-care, F: food (smell/taste), FG: feel good, H: home, Hobbies, S-Sc: social/self-care experience, M: mental, N: novelty, Ph: physical activity, S: sensory, Soc: social activity, S-Ph: social-physical item.

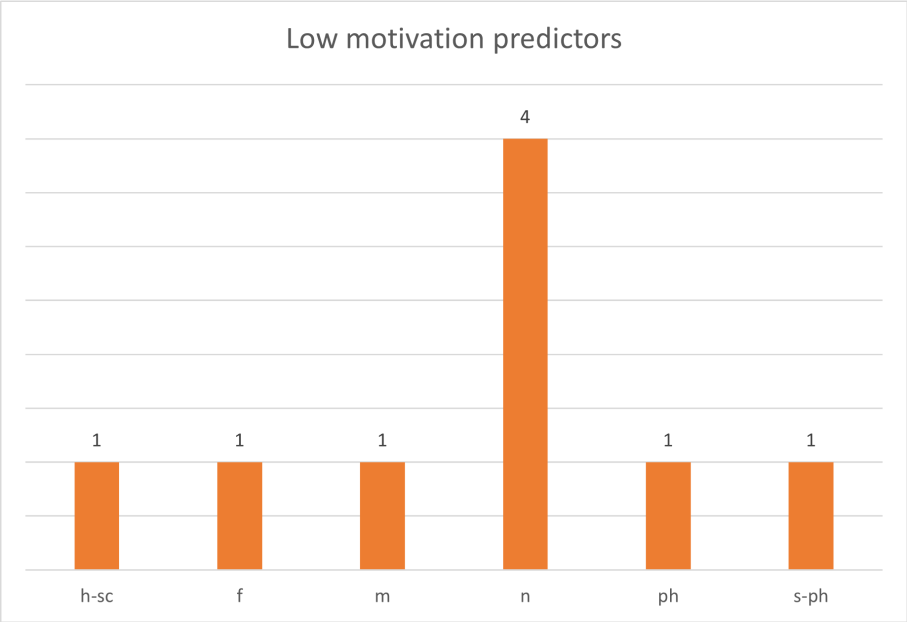

Figure 3.13 Significant predictors of low motivation level.

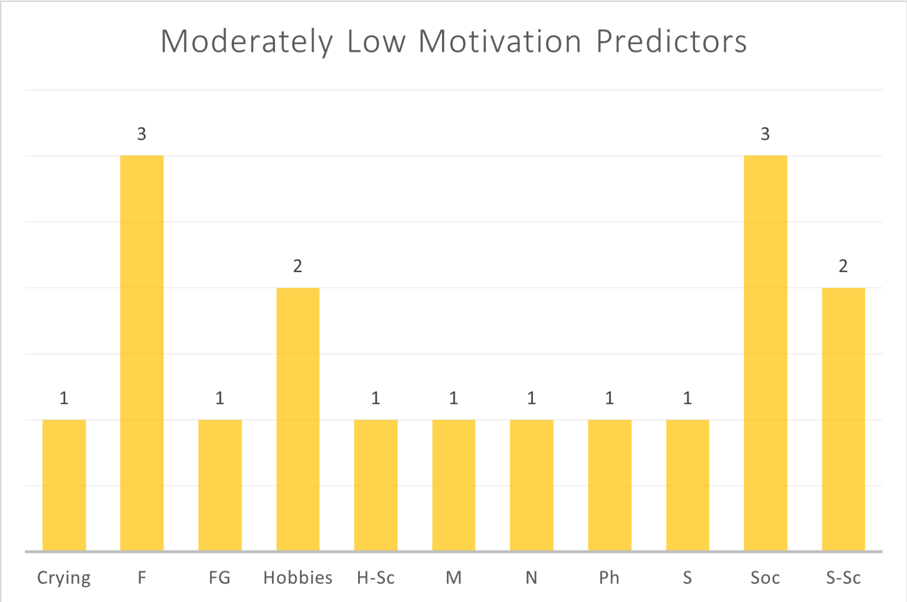

Figure 3.14 Significant predictors of moderately low motivation level.

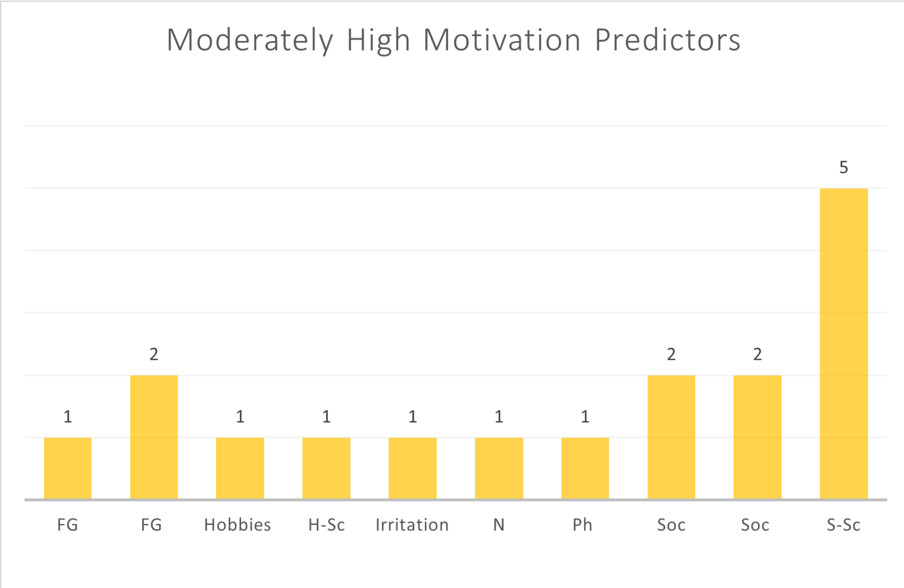

Figure 3.15 Significant predictors of moderately high motivation level.

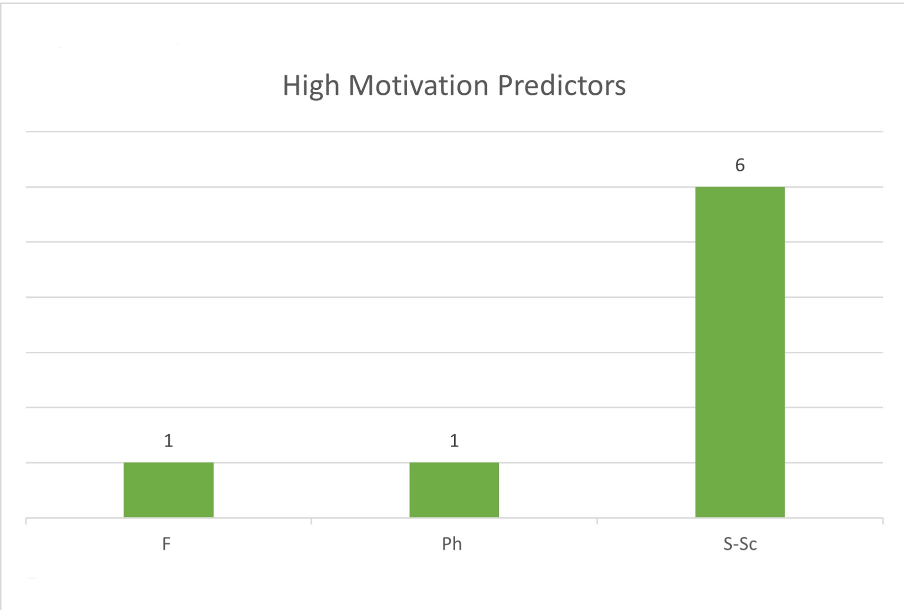

Figure 3.16 Significant predictors of high motivation level.

3.8 Model Accuracy

In this section, we tested the predictors' accuracy in predicting motivation levels. We used HEFFORT's significant predictors (n=29) we obtained from the DT analyses as input to the model to determine the predictors' accuracy in predicting the motivation level. The items we used as input are the HEFFORT (a, b, and b/a) items previously reported in Table 3.20. We split our dataset into training (60%), cross-validation (20%) and testing (20%) sets. We used split-sample validation to generalize the model and avoid over-fitting.

We obtained the model accuracy using the SPSS modeler accuracy formula based on the testing set. Analysis results are reported in Table 3.21.

$$Accuracy = 1 - \frac{|mean\ absolute\ error|}{range\ of\ predicted\ values}$$

Results showed that the prediction model's overall accuracy in the test set was 82.73% with the CHAID algorithm. Our model's analysis results are reported in Table 3.22. Prediction vs. actual results are reported in Figures 3.18. - 3.22. showing 5 different points on the predicted vs. real value plot representing very high, high, intermediate, and low b/a scores along with the model's predicted value.

Table 3.22
Analysis results for b/a scale prediction CHAID model.

Partition	**Training**	**Testing**	**Validation**
Minimum Error	-0.135	-0.193	-0.124
Maximum Error	0.155	0.143	0.176
Mean Error	0	0.004	-0.014
Mean Absolute Error	0.028	0.058	0.06
Standard Deviation	0.041	0.073	0.072
Linear Correlation	0.898	0.713	0.606

Note that:

- The linear correlation represents the Pearson Correlation between the observed value for each record and the value predicted by the model. The correlation is a measure of linear association between two variables, with values closer to 1 indicating a stronger relationship. (Correlation values range between -1, for a perfect negative relationship, and +1 for a perfect positive relationship. A value of 0 indicates no linear relationship, while a model with a negative correlation would rank lowest of all.).

- The mean absolute error in prediction = the average of the absolute values of the predicted values minus the observed values.

- The range of predicted values = the maximum predicted value minus the minimum predicted value.

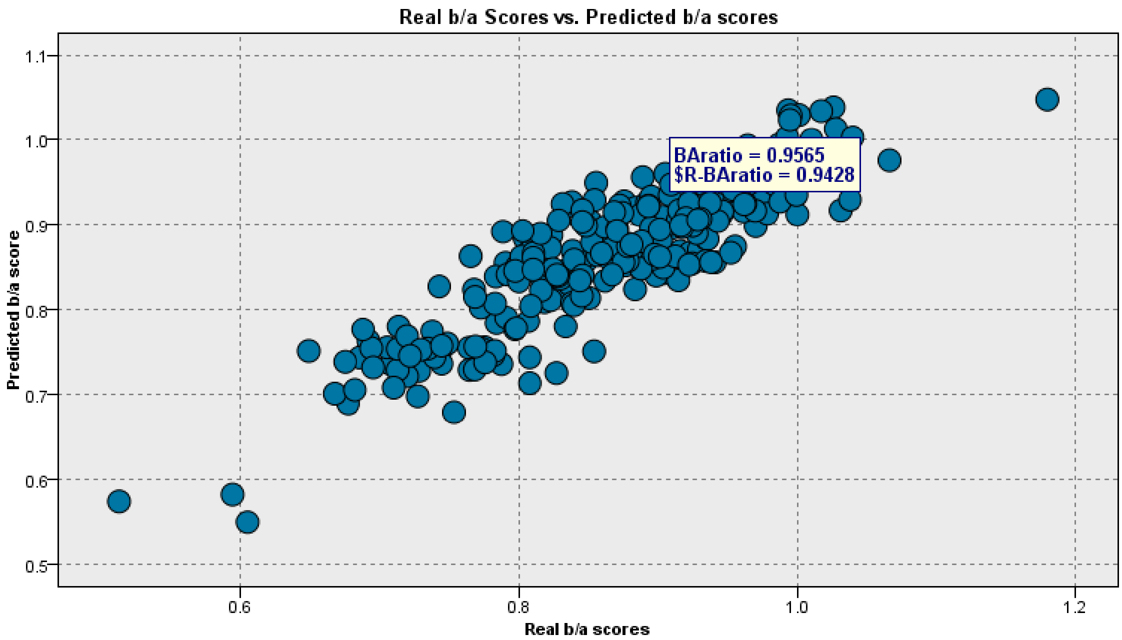

Figure 3.17 Real vs. predicted b/a score in the moderately-high motivation level.

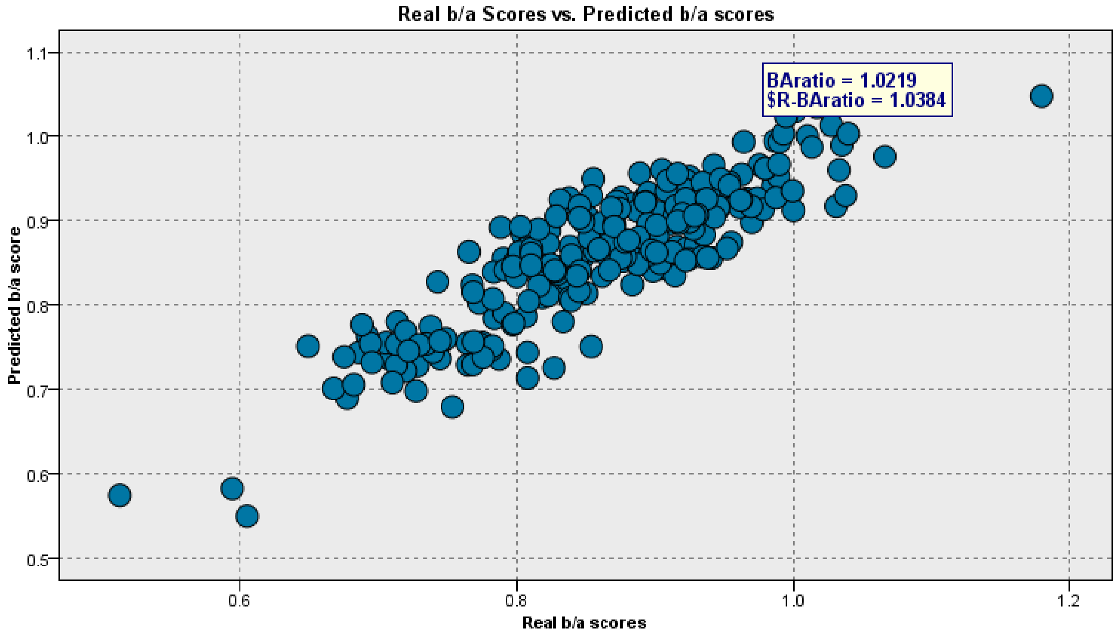

Figure 3.18 Real vs. predicted b/a score in the high motivation level.

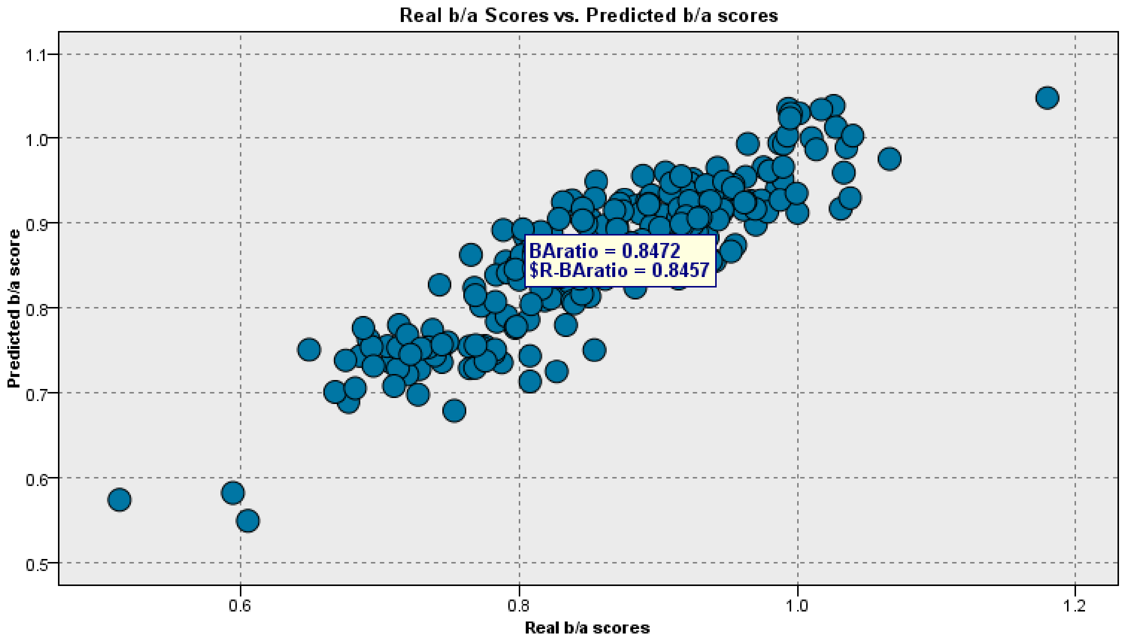

Figure 3.19 Real vs. predicted b/a score in the moderate motivation level.

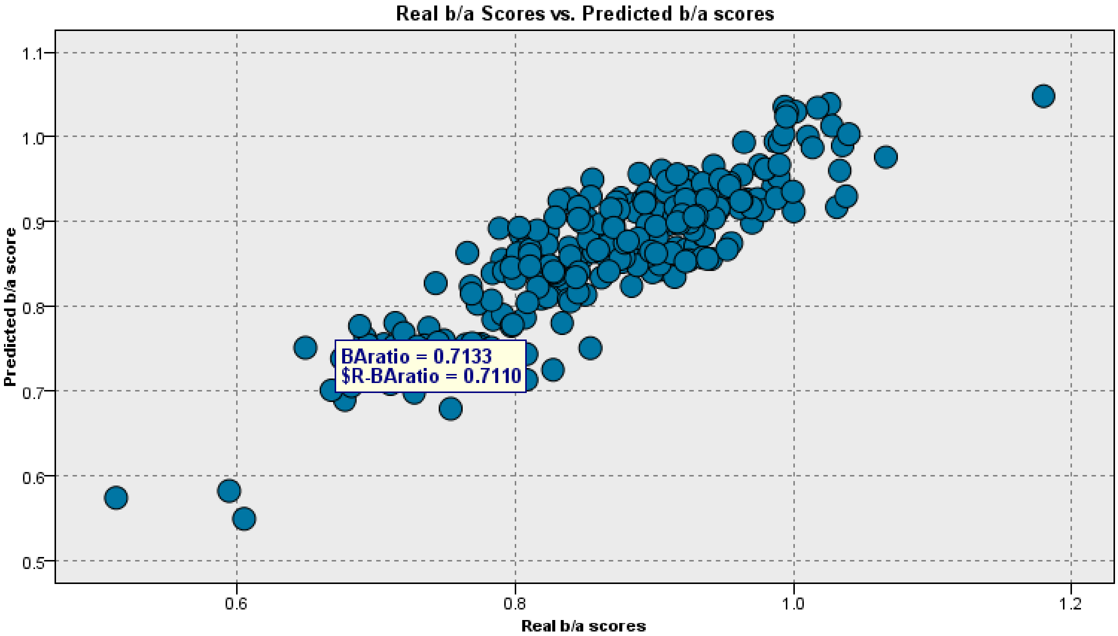

Figure 3.20 Real vs. predicted b/a score in the moderately low motivation level.

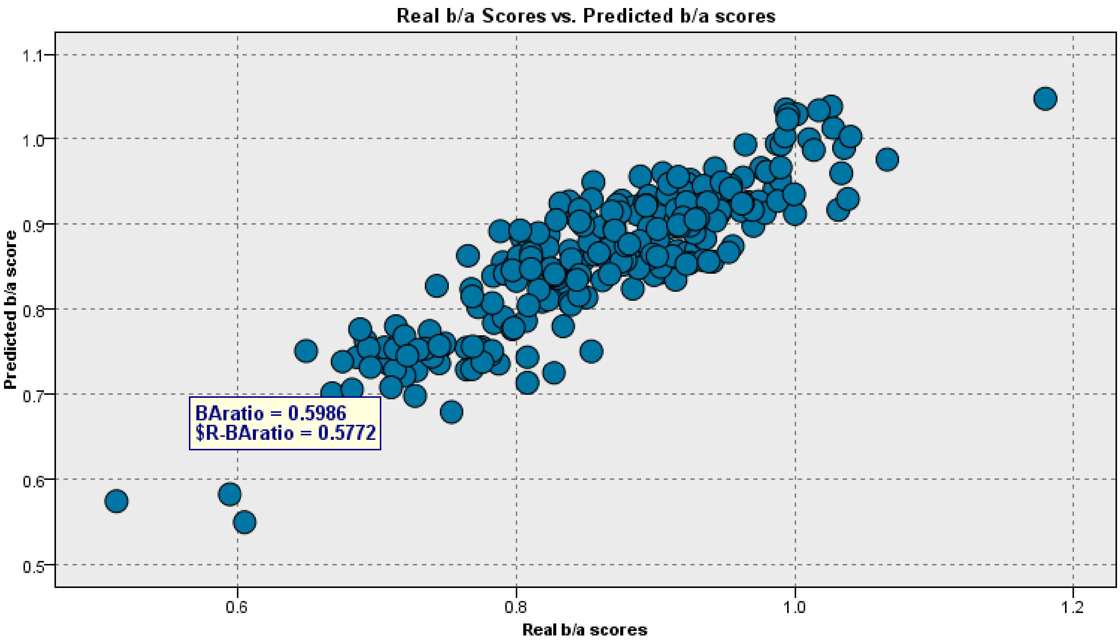

Figure 3.21 Real vs. predicted b/a score in the low motivation level.

To further investigate the questionnaires (HEFFORT and others) accuracy in predicting effortful motivation levels, we ran the CHAID accuracy algorithm on different models with different inputs. Results are reported in Table 3.23.

Table 3.23
Models' accuracy levels in predicting effortful motivation.

Model	**Items included**	**Number of items**	**Accuracy %**
1	All questionnaires included	175	86.94%
2	DT predictors from all questionnaires	53	83.45%
3	All HEFFORT items (a, b, b/a)	87	86.39%
4	HEFFORT a and b items only	58	83.82%
5	HEFFORT b/a items only	29	84.71%
6	HEFFORT (a) items	29	82.86%
7	HEFFORT (b) items	29	84.56%

4. DISCUSSION

4.1 Statistical analysis results

The current study analyzed the psychometric properties and validity using machine learning of HEFFORT, a novel questionnaire which aims to distinguish between different components of reward, namely hedonia or pleasure and effortful motivation. We found that the internal consistency of HEFFORT was high. Correlation analyses provided evidence for a separation of the sub-scales measuring pleasure and effortful motivation. A factor analysis separated HEFFORT a-items into 7 components (social/self-care, surprise/novelty, easy/feel-good, hygiene/self-care, home, smell/taste, and social/self-care activity).

4.2 Prediction results

An application of machine learning techniques revealed that individuals with high and low motivation, respectively, can be best distinguished by having high and low scores on item 25 b/a 'making home-cooked food', which is a complex behavior that requires social interactions (purchasing ingredients and sharing the food), physical and cognitive effort (thinking up recipes, purchasing, preparing, and cooking), and a motivation for self-care (eating nutritious food). Moreover, the type of items predicting low motivation (tasting sweets, gardening) were mostly (a) and (b) items, thus more relevant to pleasure than effort. On the other hand, items predicting high motivation (taking cooking classes, spending time under the sun) were mostly b/a items, therefore focused on the effort exerted on the action.

4.3 HEFFORT impact

HEFFORT is unique among questionnaires in that it aims to measure the individual components of complex psychological constructs. For example, 'reward' is known to consist of pleasure, effortful motivation, and incentive learning, which are mediated by different neurobiological systems, specifically the dopamine system which mediates effortful motivation and learning, and the opiate system which mediates pleasure. [2]. Thus, it is important to distinguish between these systems, because differential results have clinical relevance.
Comprehensibly, deficits in either system require a different treatment. However, few such tools for measuring the performance of these systems exist for humans. On top of that, no tool of those currently used can distinguish between effortful motivation and pleasure. Recently, behavioral tests like Effort-Expenditure for Rewards Task (EEfRT), behavioral measure of reward motivation and effort-based decision-making in humans, have been developed for humans based on choice tasks developed for animals [20],[21]. Although more objective, behavioral testing has its limits, since it is time consuming and typically requires lab space. Thus, the availability of a questionnaire capable of separating the components of reward, which could be used as a quick and inexpensive screening tool in research and in the clinic, would therefore be very valuable.

To address this issue and establish such a tool, we constructed HEFFORT such that effortful motivation is represented by the ratio $b/a = (a + e)/a = 1 + e/a$, where (a) symbolizes a pleasurable goal like food in the a-item 'I love food', and (b) symbolizes a compound consisting of an effortful activity that leads to a pleasurable goal, like in the b-item I cook food'. Thus, we hypothesize that the b/a ratio extracts 'effort' by removing the pleasurable goal (a) from the compound (b). This 'mathematical' approach is novel among questionnaire methods.
Typically, items are constructed to assess a complex psychological construct directly, where the individual components of the construct may not be dissociable [22].

4.4 HEFFORT subscales

In support of this hypothesis, we found that the sum of all a-items in HEFFORT correlated positively with the sum of all SHAPS items. SHAPS, in turn, measures hedonic capacity of pleasurable situations [10], and is validated by correlating it to different facets of hedonia on depression patients and healthy controls [23],[11]. Consequently, our a-items are a measurement of hedonic capacity. Next, we found that the sum of all b-items on HEFFORT, which is designed to reflect a compound consisting of pleasure + effortful motivation, correlated positively with the sum of DARS and SHAPS. DARS aims to measure 'anhedonia' or the lack of pleasure, with items measuring a mixture of different concepts (interest, motivation, effort and consummatory pleasure) mediated by different physiological components across reward domains [1]. However, unlike HEFFORT, DARS items do not separate pleasure from effortful motivation. Nevertheless, our results indicate that b-items are a measure of both pleasure and motivation. At last, the sum of all b/a-items, which aims to measure effortful motivation, correlated positively with b-items, and had no correlation with pleasure a-items. This would be expected from a valid effort scale, because b-items contain both pleasure and motivation constructs, whereas a-items exclusively measure pleasure. Together, these findings support our hypothesis that the overall b/a score measures effortful motivation independent from pleasure.

4.5 HEFFORT hedonic experiences

Additionally, we ran factor analysis for the purpose of categorizing the hedonic experiences measured by the questionnaires. For HEFFORT's a-items, we obtained 7 categories; social/self-care experiences, such as (I love kids/seaside/home-cooked food), surprise/novelty items, such as (I love tasting new foods, I love animals/nature/music), easy/feel-good items, such as (I love people/seeing people smile), hygiene/self-care items, such as (I like hygiene/fit bodies), home items (I love my home), smell/taste items, such as (I love food/bread), and finally social/self-care activities, like (I love parties/sports/swimming pools).

Our factor analysis separated SHAPS items into 3 categories, simple pleasures (reading a book, warm bath), familiar activities (seeing friends and family, enjoying a favorite meal), and external appraisal items (receiving praise, looking smart). BDI items were separated into 4 categories, negative feelings about oneself (feeling sad/guilty), cognitive-emotive items such as (feeling irritated, worrying about health), self-loathing (self-criticizing, suicidal thoughts), and somatization items (feeling satisfied, crying). DARS was already categorized [1] into 4 categories, hobbies/pastime (music, puzzles), foods/drinks, social activities (bowling, dance class, playing with grandkids) and sensory experiences (smelling coffee, seeing fireworks).

We validated these categories by running factor analysis. As for MEI, we forced the model onto three factors, in accordance with the three sub-scales of the MEI that aim to measure mental energy (making decisions, feeling overwhelmed), physical energy (exercise), and social motivation (meeting/talking to people).

HEFFORT, SHAPS, BDI and DARS factor analyses results suggest that all items are well defined into their category. However, we also found a few items which correlate with more than one category at the same time, such as item HEFFORT 22a (I love good food) which is defined as a social/self-care item, but also correlates with the surprise/novelty component. This may be due to the fact that some items may include several experiences at once, with one of the experiences dominating all others.

4.6 Machine learning application

Moreover, in this study, we used supervised machine learning algorithms, specifically decision trees to extract the characteristics of individuals scoring high and low on the b/a ratio. DT analyses have not yet been used to validate new questionnaires, but they were successfully employed to predict high and low response rates of consumer satisfaction, attitude, and loyalty [24], and also to predict customer level of satisfaction of urban interchange [25]. In the present study, we expected that the characteristics of individuals with high and low b/a scores would reflect high and low levels of motivation, respectively. Thus, we developed a predictive model in which the target variable was the overall b/a score, and the inputs were the individual items of HEFFORT, SHAPS, DARS, MEI, and BDI, and demographics. We ran DT analyses for all questionnaire items at once, for individual questionnaires, and for items selected on the basis of multiple linear regression analyses. Each analysis yielded a flowchart diagram starting with the overall b/a score as the root, and branching into smaller and smaller subsets of the data split by significant predictors until reaching the terminal node representing the final decision.

In all of our algorithm analyses which included HEFFORT b and b/a subscales, item 25 (making home-cooked food), a social/self-care item involving food, was the most significant predictor. When item 25 was not included as an input to the DT in the MLR DT analysis, we found item 16b/a (cooking), a food item, to be the significant predictor. Also, in the DARS DT analysis, we found item B6 (make an effort to get foods/drinks) to be the significant predictor, another food-related item. These results suggest that items involving "effort to make/get food" are linked to effortful motivation. Explaining this requires some speculations. We therefore hypothesize that the higher the drive to make/get food is, the higher the motivation level one has, because of an evolutionary instinct which pushes people into wanting to be on the top of survival hierarchy. Also, the action of preparing one's food can be effortful to a large degree.

Along the branches of the DTs, we found that low motivation was linked, according to our factor analysis categories, to novelty related items and internal hedonic experiences, such as tasting new foods or training dogs. As we move towards the higher motivation levels we find less and less novelty items. We found a link between moderate motivation and physical energy, such as feeling energetic, doing sports, or loving to swim. By contrast, we observe on the higher motivation branches a dominance of social/self-care experiences as well as food items, such as making home-cooked food, waking up early to see the sunrise, and making bread.

Clearly, the higher the level of energy required for an item, the higher the level of motivation predicted by the algorithm. This is observed in the type of items predicting low motivation (tasting sweets, gardening) which are mostly (a) and (b) items, thus more relevant to pleasure than effort. On the other hand, items predicting high motivation (taking cooking classes, spending time under the sun) are mostly b/a items, therefore focused on the effort exerted on the action. It is crucial to note that items in the higher energy levels are extra effortful. For example, HEFFORT items 22, and 25 (I would take cooking classes), (I make home cooked food) respectively, involve planning, preparing, and buying the food, as well as social interaction. An example of a social/self-care item is HEFFORT item 7 (I make time to be by the seaside), which involves going somewhere, being near people, sweating if it is hot, all of which require energy. So, it might be that these items are just more effortful than other items.

4.7 Similarities between HEFFORT and other questionnaires

When predicting effortful motivation represented by b/a score using decision trees, we ran a DT analysis on each questionnaire. Individual questionnaire items served as input, and the target was the total b/a score. We observed in HEFFORT and DARS analyses a dominance of social/self-care and sensory items related to foods/drinks in the primary nodes. This is because DARS measures aspects of motivation and pleasure similar to HEFFORT. This is somewhat confirmed by our Spearman correlations where we found DARS total score to correlate positively with all HEFFORT subscales total score (a, b, and b/a). For example, a complete subsection in DARS (DARS-B) refers exclusively to social activities [1]. It includes items, such as (I would be interested in doing things that involve other people), which classified together, in the combined DARS and HEFFORT factor analysis, with the with HEFFORT item (6a) (I love to be surrounded by friends) which we found to belong to the hygiene/self-care component. However, the spearman analysis results show a correlation between DARS and HEFFORT total scores. This contradicts with the factor analysis we ran on both DARS and HEFFORT which separates the two questionnaires' categories. This may be because the spearman correlations were between DARS and HEFFORT total scores, whereas the factor analysis results were based on individual items.

As for the MEI analysis, we found the primary nodes to be dominated by social activity items involving socializing with other people. An example would be item 28

in MEI, which appears in our first DT iteration, (During the past 4 weeks, to what extent were you interested in meeting new people). This difference in predictors types between MEI (social activities) and HEFFORT (novelty and self-care items) may be explained by the factor analysis we've applied on both questionnaires at the same time, where we found a clear separation between MEI and HEFFORT components. It may also be explained by the fact that MEI does not have novel or social/self-care items like HEFFORT. Instead, MEI includes physical energy items such as item 24 (how often did you exercise), mental energy items such as item 14 (did you have trouble focusing your attention on your work), as well as social activity aspects such as item 29 (were you interested in talking with others).
On the other hand, when we applied DT to SHAPS, we obtained a single item, SHAPS-1 (I would enjoy my favorite television or radio program), which had a negative correlation with the total b/a score. Thus, we did not observe a similarity between HEFFORT and SHAPS when predicting effortful motivation. This is because SHAPS measures only the hedonic aspect of an experience, regardless of one's motivation to participate in it [10].

We did not observe a relationship between HEFFORT and BDI. This might be because BDI is used to measure aspects of psychological pain like hopelessness, guilt, and feelings of being punished, or physio-somatic symptoms like fatigue, changes in appetite, and loss of libido [7],[26]. BDI correlates positively with other depression-related measures such as General Anxiety Disorder-7 (GAD-7), Center for Epidemiologic Studies Depression Scale (CES-D), and Patient Health Questionnaire-9 (PHQ-9) [27]. Hence, BDI is irrelevant to the b/a scale of HEFFORT which measures effortful motivation.

4.8 Effect of demographics on HEFFORT score

We have also examined the effect of the participants' demographics on HEFFORT by applying DT analysis to demographics (age, gender, income, education, and psychiatric drug use). We found that a person's b/a score correlates negatively with

their income level. Which means that the higher the income, the lower the b/a score. Our findings contradict with previous studies that have found income to positively correlate with life satisfaction [28]. This inconsistency may be due to one's demotivation to change their lifestyle when they are satisfied. Therefore, higher income, which correlates positively with satisfaction, correlates negatively with motivation.
Our results also contradict with another study which suggests that an employee's motivation increases with financial incentives [29]. However, another study found that emotional well-being increases with income but then reaches a plateau [30]. We find this study's result to support our results such that higher income, or reaching the plateau, does in fact decrease the motivation to obtain more money.

Likewise, we found in our DT analysis that motivation is not influenced by age except for a small sample of participants ($4<n<7$ for each age group) with people in the first (18 - 25 years) and third (34 - 41 years) age groups having higher b/a scores than other age groups. This conflicts with previous studies which suggest that older adults have higher motivation to complete cognitive tasks than younger adults (Ennis et al, 2012), whereas we found the same age group to have lower motivation in general. On the other hand, our results were consistent with other studies where they found older adults, whom we found to have lower motivation scores, to show a decline in motivation to exert effort on activities as the difficulty increases [31].

In the matter of gender, our DT analysis on demographics showed no significant influence on motivation levels except for a small sample ($n=4$ for males, $n=3$ for females) from all 272 participants, with females having higher b/a scores than males. This was consistent with previous studies measuring students' motivation levels [32] where they did not find significant difference in the global motivation score between male and female students. We also did not observe education or psychiatric drug use in any of the DT analyses nor in our multiple linear regression results. This can indicate that education and psychiatric drug use have no influence on the overall b/a score representing effortful-motivation. However, this lack of link may indicate that HEFFORT is not sensitive enough to find the effect or correlation.

These findings provide important insights about the previously used questionnaires which measure pleasure and motivation constructs. Our results show a strong correlation between HEFFORT's pleasure items and SHAPS but no correlation with effortful motivation items. On the other hand, we found HEFFORT's pleasure items to correlate with DARS, and MEI as well. Seeing that HEFFORT's pleasure items did not correlate with effortful motivation (b/a) items, this triggers a concern that some of DARS and MEI items do not clearly distinguish between effortful motivation and pleasure. We conclude that instruments to measure hedonic experiences were well represented, while instruments to measure effortful motivation were less distinct in separating effort from pleasure. This sheds a light on the critical need to have a clear separation between pleasure and motivation assessment tools for better diagnosis. This is where HEFFORT comes as a novel questionnaire capable of filling this void.

4.9 Model accuracy

Moreover, to validate HEFFORT's accuracy in measuring effortful behavior, we benefited from the same DT model which we developed for the prediction of the overall b/a score. We inserted HEFFORT's significant predictors obtained in the primary layers of the DT analyses in Table 4.1. as input to our model to predict the overall b/a score. We trained our model with 60% of our total 272 participants' data, and used 20% for cross validation and 20% for testing the model. We obtained an 82.73% accuracy based on the testing set. We have also tested the accuracy of several models with different inputs. We obtained 86.94% accuracy when all items from all questionnaire (n=175) were included, 83.45% accuracy when all DT predictors from all questionnaires (n=53), 86.39% accuracy when all HEFFORT items (n=87) were included, 83.82% accuracy when (a) and (b) items (n=58) were included, 84.71% for only b/a items (n=29), 82.86% for a items (n=29), and finally 84.56% for b items (n=29). These results show that when all HEFFORT items are included (a, b and b/a) we have the highest accuracy level in predicting effortful motivation. The difference in accuracy percentages may be due to the number of items entered as input to the model, such that random error decreases with a larger number of items.

In the context of psychiatric questionnaires, our validation method using decision trees is the first of its kind. Using decision tree algorithms, we were able to explore the relationships between HEFFORT and other questionnaires and find links, correlations, and areas of development, identify participants' features based on their total HEFFORT score, and give an unbiased estimate of the final model's accuracy. Evaluating our model's accuracy in comparison to other applications in the psychiatric field is not possible as there are no studies using the same methods in our study. Nonetheless, we compared our model's accuracy with other applications that use decision trees in survey analysis such as bank crediting applications [33] where the models' accuracy was 94%, or consumer satisfaction surveys [24] where the accuracy was 78%. We can say that our model's accuracy (82.73%) is considered very good. Furthermore, we were able to test HEFFORT on a virtual testing set instead of collecting new data in face-to-face interviews, which would have been hard and risky due to the COVID-19 global pandemic.

Based on our model's accuracy results, we can safely assume that HEFFORT's items are valid predictors of one's motivation level and that HEFFORT is an efficient tool in separating motivation from pleasure. Which is what we have hypothesized in the first place. Likewise, we expected HEFFORT's pleasure (a) items to correlate with SHAPS as both are intended to measure hedonic experiences. In the same manner, we expected the effortful motivation (b/a) items to not correlate with any pleasure items, which was the actual result and the purpose of developing HEFFORT.

Regarding participants' features, we speculated income to be a significant predictor of motivation, but in contrast to our speculations, we found income to correlate negatively with motivation levels. We have also speculated physical activity items, since they require more effort, to play a bigger role in predicting motivation but the results did not show major significance of those items.

5. LIMITATIONS AND SUGGESTIONS

In this study, we have introduced the novel HEFFORT questionnaire, explained the b/a scale's design, properties, and derivation, and benefited from machine learning techniques in validating and testing its reliability and confidence. We were faced by a few limitations. The study evaluated the general population's responses on the used questionnaires, which gave us very typical and expected HEFFORT final score results. With a little number of people who have very high motivation levels such as athletes or children, or very low motivation levels, such as depression patients, we were not able to clearly predict the features of those groups in specific.

In the context of this study, we were able to answer the question whether HEFFORT is a valid tool of effortful motivation measurement, we were also able to provide insight on the features of people with different motivation levels.
On a broader scope, HEFFORT shows a promise in being the first tool to measure effortful motivation, demonstrating higher specificity to effort than to pleasure in comparison to DARS and MEI which measure similar constructs. Additionally, this study shows the contribution of machine learning in facilitating clinical psychiatry research, which will aid researchers in this domain during their crucial tasks of analysis and diagnosis. Future testing and use can establish HEFFORT as a research and clinical diagnostic tool that assesses different components of reward.

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