How Sleep Moderates the Implicit Affective Feelings of Energy and Physical Activity

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Abstract

This research focuses on the implicit and explicit affective appraisals regarding exercise to find out why exercise behavior is declining. It focuses on the affective experience regarding energy, whether people associate energy or tiredness with sports. Sleep plays an important role in feeling energized and is therefore important to take into account. This gives the research question, to what extent does sleep quality moderate the relationship between the amount of physical activity and implicit core affective exercise experiences for the construct energy-tiredness?

To answer this question, cross-sectional qualitative research was done. To measure implicit affective appraisal an SC-IAT was made, to measure the explicit affective appraisal the AFFEXX was used, to measure physical activity the IPAQ-SF was used and to measure sleep quality the PSQI was used. Participants were found through convenience sampling through social media, SONA system, and friends and family.

There was no significant correlation between the implicit and explicit affective appraisal ($r(59) = -0.18$, $p = .157$). Therefore, the focus was on the implicit affective appraisal. However, implicit affective appraisal was not associated with exercise ($F(1, 59) = 0.411$, $p = .524$) and sleep did not moderate this relationship ($\beta = -490$, $p = .661$).

The results illustrated that sleep does not moderate the relationship between physical activity and implicit affective exercise experience. From this we know that just one affective appraisal does not have enough strength to predict physical activity.

Key words: Affective Appraisals, Netherlands, cross-sectional questionnaire, Sleep, Exercise

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Introduction

Physical activity is of vital importance to human health. According to the World Health Organization (WHO, 2022), over 1.4 billion people worldwide do not meet the minimum requirement for physical activity. The recommended amount of physical activity is at least 150 minutes of mild exercise per week or 75 minutes of intensive exercise per week (WHO, 2022). People who adhere to these standards experience a decrease in disorders like depression and anxiety, diabetes type 2, site-specific cancer, and hypertension, and a decrease in all-cause mortality (WHO, 2022). Physical activity also improves cognitive health and improves sleep quality (WHO, 2022). Therefore, it is important to understand why people are not physically active.

Most behavioral change theories focus on cognitive parameters to explain behavior (Ajzen, 1991). However, these approaches have proven to be generally unsuccessful, sedentary behavior is rising and more people are not physically active enough (WHO, 2022). According to Ekkekakis (2012), a better way of trying to change physical activity level is to look at the affective responses to exercise. People who have a negative core affective valence during exercise will avoid it in future situations. Thus, people are seeking pleasure and avoid displeasure. In the Affective Reflective Theory (ART) is postulated that core affective exercise valence may influence deliberative reasoning about exercise engagement and effort. And this core affect may have a direct impact on behavior through behavioral urges. The ART theory explains that how someone feels about physical activity can influence how they think about it and how much effort they are willing to put in. These feelings can also directly impact the actions people take to be physically active or not.

The ART theory is an example of a theory regarding the decision-making process. Human decision-making can be explained by the dual-processing approach. Type 1 process in decision-making is fast, automatic, and unconscious, type 2 decision-making is slow deliberate, and conscious (Evans, 2008). Type 2 processing requires attention, reasoning, and working memory capacity, especially when someone tries to change their behavior (Brand & Ekkekakis, 2018). Everyday decisions seem to be made automatically. When someone is used to not going for a walk daily, their type 1 processing will make the decision automatically (Evans, 2008). Since it is an automatic process, it is difficult to change, and people would need a lot of effort to do so (Strobach et al., 2020). Adding to this, the automatic decision usually makes sense to people, so there is no perceived need to change it (Strobach et al., 2020). Even when type 2 is active and a person is aware that they should increase their physical activity, type 1 is still opposing this which results in a conflict between type 1 and type 2 processing (Evans, 2008). This conflict can result in cognitive errors and biases within decision-making (Evans, 2008). The decision to be made usually favors type 1 processing since it is the easy and familiar way of doing things (Brand & Ekkekakis, 2018). This bias towards type 1 processing results in continuing the unwanted behavior even when people consciously want to change it.

One aspect that has not been researched often is the effect of sleep on the decision to be physically active. It is proven that physical activity increases the quality and amount of sleep (Alnawwar et al., 2023; Kredlow et al., 2015; WHO, 2022). However, more research is indicating that it works both ways. People with better sleep quality tend to do more exercise as well (Holfeld & Ruthig, 2014). People tend to be less active when they experience a worse quality of sleep, compared to when they have a better quality of sleep (Mead et al., 2019). The causal effect of physical activity on improving sleep has been researched thoroughly. However, the other way around; the causal effect of sleep quality on physical activity, has not been researched that much. There is a clear connection between physical activity and sleep, so far, the results indicate that this connection is bidirectional.

Sleep is one of the most important aspects of our life. It can have detrimental effects on health when someone has poor sleep quality or insufficient amount of sleep. A good quality of sleep means that the sleep latency is <45 minutes, there is no more than 1 awakening of >5 minutes and the total awakening time is <21 minutes per night, the sleep efficiency, the ratio between time in bed trying to sleep and sleeping, is higher than 85% and at least 21% of sleep is Rapid Eye Movement (REM) sleep (Ohayon et al., 2017). Inadequate sleep can cause a range of disorders, including mood disorders like depression and anxiety, dementia and other neurodegenerative disorders, hypertension, cardiovascular diseases, immune impairment, and even loneliness (Worley, 2018). Too little sleep causes a decrease in alertness, memory fade, and emotional deregulation (Worley, 2018). Too little sleep and bad sleep quality are also found to impair the working memory and decision-making processes (Alhola & Polo-Kantola, 2007), decrease motor skills (Ayalon & Friedman 2008), impair problem-solving skills, and decrease the effect of the inhibition mechanism of the brain (Durmer & Dinges 2005). People are often not aware of these unconscious effects of sleep deprivation, and therefore never consider that this could be a reason that they cannot change unwanted behavior.

Measuring whether unconscious processes are related to decision-making is important since it is an essential step in understanding how to effectively change behavior (Hagger, 2016). Sometimes, people know that they are not active enough and need to change their behavior, however, unconscious processes prevent them from doing so (Brand & Ekkekakis, 2018). They consciously want to change their behavior, however, they unconsciously are influenced to not change their behavior (Brand, 2008). This can have all kinds of reasons that are not known yet. The unconscious is difficult to measure because people are not aware of it, therefore, this research will focus on finding associations and not on finding ways to change it.

To measure the unconscious, this research will administer an Implicit Association Test (IAT) (Greenwald et al., 1998). This test measures implicit biases and unconscious attitudes toward certain beliefs (Greenwald et al., 1998). Implicit biases are automatic associations towards certain things. People unconsciously link obesity with inactivity, even though this might not be true. These associations are formed through interactions with for example family and friends, media and culture, and what has been taught in school (Brownstein & Zalta, 2019). The IAT measures these beliefs by pairing two groups of words. People must categorize words according to pre-designated categories. For example, one category has good and bad words, and the other category has active and inactive words. An example of a good word could be fun, and an example of a bad word could be boring. An inactive word could be sitting, and an active word could be running. They need to do two categorization tasks presented in congruent and incongruent blocks. In a congruent block the words are categorized according to their inherent evaluation (e.g., good words with active words). The incongruent blocks pair words with opposing evaluations (e.g., good words with inactive words). The reaction time is measured to see if there is a bias to a certain combination. It can also only be one-sided, so only good and bad words and active words (Karpinski & Steinman, 2006).

In this research, the words used in the IAT are related to The Affective Exercise Experiences (AFFEXX) questionnaire categories. The AFFEXX is a questionnaire that measures conscious affective appraisals toward physical activity (Ekkakakis et al., 2021). This means that it tries to gain insight into how people look at physical activity and what their attitudes toward physical activity are (Ekkakakis et al., 2021). The questionnaire consists of 36 items which are grouped into six antecedent appraisals and three core appraisals (Ekkekakis et al., 2021). The focus of this research will be on the core appraisal of energy vs. tiredness. This core appraisal measures whether people feel energized when they do exercise, or if they feel more fatigued and exhausted. It is measured by several statements, an example of a statement is ‘Exercise is very invigorating – Exercise is very tiring’ and participants have to say how much they agree or disagree (Ekkakakis et al., 2021). The AFFEXX is used to measure what people explicitly think of exercise. To measure what people implicitly think, an IAT will be used. The IAT will be a Single Category IAT (SC-IAT) since this research only measures activity and not inactivity. Therefore, only one category to link the energy vs. tiredness words is needed.

This research aims to find out if the unconscious energy vs. tiredness affective appraisals that are measured with the SC-IAT are in line with the conscious affective appraisals measured by the AFFEXX. It will investigate the effect of the implicit affective appraisal on physical activity and how sleep influences this relationship between unconscious affective appraisal and physical activity.

This study will explore the gap around the relationship between conscious and unconscious affective appraisals towards physical activity and the influence of sleep. To fill this gap this research will address the following questions:

a. To what extent are the implicit and explicitly core affective exercise experiences correlated for the construct of energy-tiredness among students and residents in The Netherlands?
b. To what extent are the implicit core affective exercise experiences for the construct energy-tiredness associated with the physical activity level of students and residents in The Netherlands?
c. To what extent does sleep quality moderate the relationship between the amount of physical activity and implicit core affective exercise experiences for the construct energy-tiredness among students and residents in The Netherlands?

Following the research questions the specific hypotheses are as follows:

1. People who consciously associate physical activity with tiredness will unconsciously also associate physical activity with tiredness.

1.1 People who consciously associate physical activity with energy will unconsciously also associate physical activity with energy.

2. The less the unconsciously energized a person feels, the less likely they are to be physically active in any way.
3. Sleep will act as a moderator variable. People who unconsciously want to be physically active will not when they have lower sleep quality.

Methods

Design

This is cross-sectional quantitative research. This design was chosen to gain a sample with as much power as possible. A big sample size makes sure that small and moderate effects can be studied. This research also aims for a varied sample of people from different social-demographic situations, ages, genders, and nationalities. By having cross-sectional quantitative research, the opportunity of getting a varied and large sample is highest.

Participants

Included participants had sufficient knowledge of the English language and were aged 18 or above. 112 people participated in the study, of which 40% were male, 58% female, and 2% other. The age of the participants ranged from 18 to 69 (M = 26, SD = 11). 56% of the participants were Dutch, 22% of the participants were German, and 22% of the participants had another nationality. There were no exclusion criteria, only people who did not finish the complete questionnaire were excluded from the sample. The sampling was done by convenience sampling through the SONA system of the University of Twente. SONA is a system of the University of Twente that allows students to gain points by participating in the studies of other students from the university. The sampling was also done through convenience sampling through social media including Facebook, Instagram, and LinkedIn, and by contacting people in our close environment. The participants were asked to tell people they knew to fill in the questionnaire, so more participants were recruited through snowball sampling.

Materials

Affective Exercise Experiences

The Affective exercise experiences were measured with the Affective Exercise Experience Questionnaire (AFFEXX) (Ekkekakis et al. 2021). This questionnaire has 36 items that measure three core affective experiences and six antecedent cognitive appraisals. The three core affective experiences are energy/tiredness, tension/calmness, and pleasure/displeasure. The core affective appraisals have four items in the questionnaire each. The six antecedent cognitive appraisals are liking vs. disliking group exercise, showing off vs. shying away, empowerment vs. damage, pride/honor vs. shame/guilt, competence vs. incompetence, and interest vs. boredom. The antecedent cognitive appraisals have three items each, except for competence vs. incompetence, which has four items. One item has two statements opposite to each other, the participant has to rank with which one they agree on a 7-point Likert scale. Scoring 1 means completely agreeing with statement A and scoring 7 means completely agreeing with statement B. An example of two opposite statements regarding the energy vs. tiredness appraisal is: on side A “Exercise leaves me feeling exhausted” and on side B “Exercise leaves me feeling energized”. Scoring 1 means completely agreeing with statement A which signifies scoring high on the tiredness side of the energy vs tiredness appraisal. Scoring 7 means completely agreeing with statement b which signifies scoring high on energy on the energy vs tiredness appraisal.

Ekkekakis et al. (2021) found that the AFFEXX presents high convergent validity and good internal consistency for all appraisals ($\alpha = 0.80$). They also showed that there is a good correlation within all the appraisals ($\alpha = .78$ to $\alpha = .88$). With the core appraisal energy vs tiredness having an .86 correlation.

Implicit affective experience

The implicit association between physical activity and the core affective appraisal of energy/tiredness was measured with a Single Category Implicit Association Test (SC-IAT) (Greenwald et al., 1998; Karpinski & Steinmann, 2006). To make the SC-IAT, SoSci software was used.

A SC-IAT consists of two parts, or tests. The first test pairs the energy words (energizing, strength, power, motivation, active, full of energy, drive, energetical, and endurance) with the physical activity words (cycling, running, weightlifting, swimming, jogging, bootcamp, and working out) in one category and the tiredness words (exhausted, sore, tired, fatigues, weakness, sleepiness, drained, slow, and heavy) in the other category. To group to the category energy and physical activity the participant presses on a key on the left-hand side of the keyboard, in this case, the 'E' key. On a touch screen device, the participant presses on the left-hand side of the screen. To add to the tiredness category, the participant presses a key on the right-hand side, in this case, the 'I' key. On a touch screen device, the participant presses on the right-hand side of the screen. 96 times, a random word from any of the three categories pops up, 72 times this is a test round, and 24 times it is a practice round. The participant does not know which one is practice and which one is test. The second test has one difference, instead of adding the physical activity words and the energy words in one category, the participant has to add physical activity words to the tiredness category. The energy words are still on the 'E' key, but the physical activity words are added to the 'I' key with tiredness words.

The SoSci software then automatically calculates the d-score of the participants. The d-score can be positive or negative, ranging from 1 to -1. In general, the closer to 0 the weaker the association (Bhandari, 2020). In this case, a negative d-score means that the participant is relating physical activity with tiredness, whereas a positive d-score means the participant relates physical activity more to energy. Generally, a d-score of 0.2 is considered a small effect size, 0.5 is considered a moderate effect size, and 0.8 or higher is considered a large effect size (Bhandari, 2020).

Karpinski & Steinman (2006) were the first to make an SC-IAT, they found a reliability of .61. They also found that an SC-IAT has sufficient group validity, convergent validity, and predictive validity. They also found that the SC-IAT has reasonable internal consistency (r = .69).

Sleep quality

The sleep quality is measured with the Pittsburgh Sleep Quality Index Questionnaire short version (PSQI-SF) (Fomodu et al., 2018). It is a self-report questionnaire, meaning that the participants have to fill in the questionnaire based on their perceptions. The participants are asked to look back on the past month and base their answers on it. The questionnaire has 13 items that measure five different aspects of sleep quality. These five aspects are sleep duration and efficiency, sleep latency, sleep disturbance, waking up in the middle of the night, coughing and snoring, and daytime dysfunction. For the first four items of the questionnaire, the participant is required to insert a time or duration in a text field. An example of an item is 'During the past month, what time have you usually gone to bed'. For the other 9 items, the participants can fill out a 4-point Likert scale ranging from 0 to 3 points. 0 points means not during the past month, 1 means less than once a week, 2 means once or twice a week and 3 means more than three times per week. An example of an item is: 'During the past month, how often have you had trouble sleeping because …'. The participant answers this on the 4-point Likert scale.

The scoring key made by Fomodu et al., (2018) was used to calculate the global score of the PSQI-SF. This global score ranges from 0 to 18 points. When the score is higher than 4, the participant is considered to have poor sleep quality (Fomodu et al., 2018). Fomodu et al. (2018) found a diagnostic sensitivity of 83.4%, this means that the PSQI-SF can identify 83 poor sleepers out of 100. They also found a specificity of 97.4% ($p < .001$), meaning that the PSQI-SF rarely labels someone as a poor sleeper when they are not.

Physical activity

To measure physical activity the International Physical Activity Questionnaire Short Form (IPAQ-SF) was used (Craig et al., 2003). The IPAQ-SF is a self-report questionnaire that lets participants fill in exactly the number of hours and minutes they spent doing physical activity in the past week. The IPAQ-SF differentiates between vigorous, moderate, and light exercise. The total physical activity is calculated with the help of the Metabolic Equivalent of Task (MET). This means that light, moderate, and heavy physical activity counts differently towards total physical activity done by a person. Heavy physical activity has 8,0 METs, moderate physical activity has 4,0 METs and light physical activity has 3,3 METs. The participants report the number of minutes they do each type of physical activity as well as how many times per week. To calculate the total physical activity of a participant, how many times per week is multiplied by the number of minutes per time and then multiplied by the corresponding METs. This is done for all three forms of physical activity. A highly active person would get >3000 METs per week, a moderately active person would get >600 <3000 METs and an inactive person would score <600 METs (Forde, 2018).

Lee et al. (2011) did a literature search and they found sufficient validity for the IPAQ-SF. They also found that the people filling in the IPAQ-SF overreported the amount of physical activity by an average of 106%. Craig et al. (2017) found good reliability with $\alpha = 0.80$.

Procedure

Before the administering of the survey to the participants, ethical approval was needed. After receiving ethical approval (number 240366) from the BMS Ethics Committee at the University of Twente, recruiting participants via SONA, social media, and face-to-face started. When the participants received the link to the online survey, The first thing they saw was an informed consent form (see Appendix A). Once the participants consented, they continued with the survey, when they did not consent, they did not have to fill in the survey. After the informed consent was signed, they answered some general demographic questions. This includes age, gender, nationality, language, marital status, living area, and occupation. This was followed by the AFFEXX, PSQI-SF and IPAQ. The online questionnaires were administered in random order to prevent one questionnaire from always being first, which could lead to biases. After the online questionnaires were filled in, the participants did a single-category IAT. These were also in random order to prevent any biases. Participants took on average 32 minutes to complete the whole survey. At the end, participants were thanked for participating. The data collected was stored in UTwente One Drive and deleted after the data analyses were complete. All data is anonymous, and the participants could not be traced back from the answers they filled in. Only the researchers had access to the data.

Data-analysis

For the data analysis R studio version 4.1.1 was used. The data was imported from SoSci software as a CSV file. The code used for the full data analysis can be found in Appendix F. The dataset contained variables from questionnaires that were of no use, so the first step was to delete all unnecessary variables. To calculate the explicit affective exercise experience score, four questions from the AFFEXX were used. These 4 items were merged into one overall score. The SoSci software already calculated the d-score for the implicit affective experience before importing it into R, so no calculating was necessary. The sleep quality had 13 items which were calculated into one overall score according to the scoring key of Fomodu et al. (2018). The physical activity had six items that were used to calculate the overall MET minutes, the MET minutes served as the overall score of physical activity.

A total of 51 cases were deleted from the dataset. The SC-IAT had 40 missing d-scores that had to be excluded. A software error in the sleep quality questionnaire caused 8 cases to be excluded. The software error allowed the participants to fill in more than one answer on the sleep quality questionnaire. Typos and unrealistic time estimate on the physical activity questionnaire caused 3 cases to be excluded from the physical activity questionnaire. After all the exclusions, a total of 61 cases were included in the data analysis.

To get a look into the sample, before doing the analysis for the hypotheses, the descriptives were calculated and reported in a table.

Hypothesis 1 – Difference Between Implicit and Explicit Affective Appraisal

Hypothesis 1 investigates the extent of the differences between implicit and explicit core affective appraisal energy-tiredness. To find the relationship between the implicit and explicit affective appraisal of energy-tiredness, a bivariate correlation test needed to be done. Both the AFFEXX and the SC-IAT are needed to do this analysis. In order to do the analysis, it was necessary to know on which level the variables are calculated, interval or ratio. Before being able to do the analysis, normality for both variables needed to be tested as well. This was done by making a Q-Q plot of normality. When it proved to be normal, and the variables were on the same level, a parametric test was done, in this case, the Pearson test. If there was no normality or there was a different level of measurement, a non-parametric test was done, in this case, a Spearman test.

Hypothesis 2 – Association Implicit Affective Exercise and Physical Activity

Hypothesis 2 investigates the association between implicit affective exercise and physical activity level. To test this hypothesis a linear regression of SC-IAT and IPAQ was done. The SC-IAT is the independent variable and the IPAQ is the dependent variable. To do the linear regression, four assumptions needed to be checked first. These assumptions are normality of the variables, homoscedasticity of the residuals, linearity of the residuals, and independence of the variables. Normality was checked with a Q-Q plot of normality, homoscedasticity was tested by plotting the residuals vs. the fitted values, linearity was checked by making a scatterplot of the residuals, and independence was assessed by doing a Durbin-Watson test. If all of these assumptions were met, linear regression could be done. If linearity was not met, a logarithmic transformation of the residuals was done to increase linearity. When linearity was still not met after the logarithmic transformation, or when another assumption was violated, a non-parametric test needed to be done, in this case, a Spearman test.

Hypothesis 3 – Sleep quality moderation

The third hypothesis aims to find out if sleep quality moderates the relationship between physical activity and implicit affective exercise. This was done by taking the linear regression from hypothesis two and adding a moderator variable. The implicit affective exercise is the independent variable physical activity is the dependent variable and sleep quality is the moderator value. Sleep quality is the interaction variable in the linear regression of implicit affective exercise and physical activity. To see if sleep quality plays a moderating role, the explained variance (R square) of the linear regression model of hypothesis 2 was compared to the moderator analysis.

The assumptions for linear regression needed to be tested again, this time adding the multicollinearity test. Multicollinearity is tested with a Variance Inflation Factor (VIF) test. When linearity was violated, a log transformation was done to make the variable more linear. If this did not improve linearity, or if any of the other assumptions were violated, the physical activity variables were changed into two categories (active-inactive) for the moderator analysis. The cut-off score for active or inactive was done by doing a median split.

Results

The descriptives of the physical activity, affective exercise experiences, sleep quality, and implicit affective experience are shown in Table 1. The sample used for this research proved to be highly physically active since the average MET scores on physical activity are >3000. However, the sleep quality of the sample on average was poor since 54% of participants had more than 4 points on the sleep quality questionnaire. Most people in the sample implicitly associated exercises with energy since most scores were >0. Explicitly, the sample was more inclined to the energy side as well.

Table 1

Descriptives of the sample (n=61)

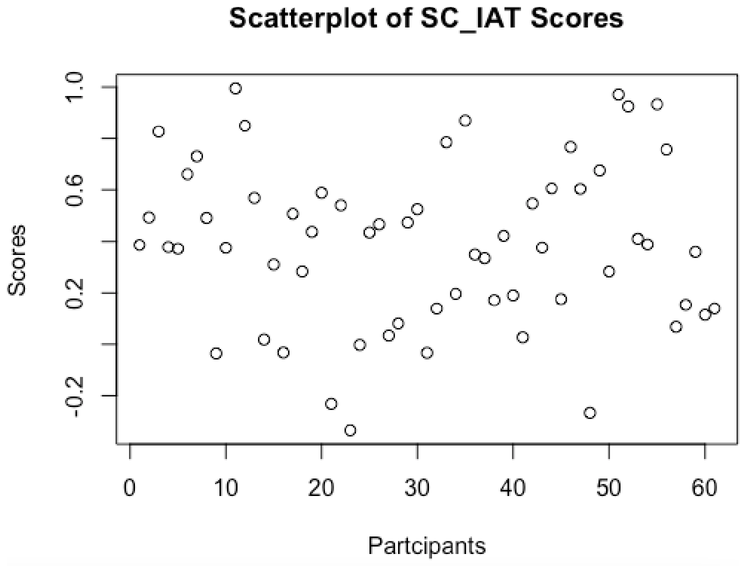
	M	*SD*	Min.	Max.	Median
Physical Activity	4149	2684.5	0	16506	3932
Sleep Quality	4.7	2.1	0	11	5
Explicit Affective Experience	5	1.2	1	7	5.3
Implicit Affective Experience	0.4	0.3	-0.3	0.99	0.4

Note: *M* = mean, *SD* = standard deviation, Min. = minimum score, Max. = Maximum score

Figure 1 shows how the scores of the SC-IAT are distributed. There are very few negative scores, which means that the people in the sample implicitly link exercise with feelings of being energized.

Figure 1

Scatterplot of the scores of the SC-IAT which measures implicit affective exercise



Note: The x-axis is the participants, and the y-axis is the score per participant.

Hypothesis 1 – Difference Between Implicit and Explicit Affective Experience

To test the first hypothesis a Pearson correlation analysis is done. The variables that measure explicit affective exercise experiences, as well as the variable that measures implicit affective experience have an absolute 0, they are ratio variables. The Q-Q plot also indicates that both variables follow a normal distribution since they follow the reference line almost perfectly (see Appendix B1 & B2). The relationship between explicit affective exercise experiences and implicit affective experience is not significant ($r(59) = -0.18$, $p = .157$). This means that people who explicitly feel tired or energized, do not necessarily feel tired or energized implicitly.

Table 2

Correlation analysis

Variable	1	2	3	4
1. Physical Activity	-			
2. Sleep Quality	-.19*	-		
3. Explicit Affective Exercise	-.09**	-.10***	-	
4. Implicit Affective Experience	.08^	-.08^^	-.18^^^	-

*p = .14 **p = .50 ***p = .46 ^p = .52 ^^p = .52 ^^^p = .16

Hypothesis 2 – Association Implicit Affective Experience and Physical Activity

To test hypothesis 2, a linear regression between implicit affective exercise and physical activity is done. Table 2 shows that there is no significant correlation between implicit affective exercise and physical activity. First, the variables were inspected for normality by making a Q-Q plot (see Appendix B1 & B3). This plot showed that the variables are normally distributed since they follow the reference line almost perfectly. To assess whether there was homoscedasticity, a plot was made with the residuals (see Appendix C1). The plot showed that the scores were randomly scattered around the x-axis, meaning there is homoscedasticity. In addition to this, a Breusch-Pagan test was done, which proved that there was homoscedasticity as well (p = .610). To test if there were violations of independence, a Durbin-Watson test was done. The test gave a dw = 2.37 with a p = .929. This shows no violation of independence. Lastly, to check linearity a plot was fitted with a linear relationship scatterplot (see Appendix C2). This plot underwent one logarithmic transformation of the physical activity variable to ensure linearity. After the logarithmic transformation, the scatterplot was linear.

Since all assumptions of linear regression are met, a linear regression was done to examine the effect of implicit affective experience on physical activity.

The regression model was statistically insignificant, F(1, 59) = 0.411, p = .524. The model explained <0.001% of the variance in physical activity. This means that there is no relation between physical activity and implicit affective experience.

Table 3

Regression Results

Physical activity	Standardized Coefficient	Coefficient	Standard Error	*t*-value	*p*-value
Intercept	-	3760	946	3.97	$\leq$ 0.005
Implicit Affective Experience	0.08	1217	1899	0.64	0.534

Hypothesis 3 - Sleep as a Moderator for the Linear Regression

To test hypothesis 3, the linear regression from hypothesis 2 is used with an extra moderator value, sleep quality. Table 2 shows no significant correlation between sleep quality and physical activity and no correlation between sleep quality and implicit affective exercise. First, the sleep variable was checked for normality with a Q-Q plot (see Appendix B4). This plot showed that sleep quality is normally distributed since it follows the reference line almost perfectly. To assess whether there was homoscedasticity, a plot was made with the residuals (see Appendix D1). The plot showed that the scores were randomly scattered around the x-axis, meaning there is homoscedasticity. In addition to this, a Breusch-Pagan test was done, which proved that there was homoscedasticity as well (p = .853). To test if there were violations of independence, a Durbin-Watson test was done. The test gave a dw = 2.41 with a p = .946. This shows no violation of independence. Lastly, to check linearity a plot was fitted with a linear relationship scatterplot (see Appendix D2). This plot underwent one logarithmic transformation of the physical activity variable to ensure linearity. After the logarithmic transformation, the scatterplot was linear. Lastly, multicollinearity was tested by running a correlation matrix, it was intended to do a VIF analysis, however, this did not work in R. The correlation matrix showed that there was no multicollinearity (-0.084).

Since all assumptions are met, a moderator analysis was done to examine the effect of implicit affective experience on physical activity moderated by sleep quality.

The initial regression model without the moderator variable was not significant F(1, 59) = 0.411, p = .524. The model explained <0.001% of the variance in physical activity. After adding sleep quality as a moderator variable, the model was also not significant F(3, 57) = 0.90, p = .448. The model explained <0.001% of variance. This shows no significant difference between the two models.

No main effect was found for implicit affective experience (β = 2854, p = .545) as well as for sleep quality (β = -270, p = .592). This means that there is no significant association between implicit affective experience and sleep quality on physical activity.

No interaction effect was observed between sleep quality and implicit affective experience (β = -490, p = .661). This means that sleep quality does not change the relationship between physical activity and implicit affective experience relationship.

Table 4

Moderation Results

Physical activity	Estimate	Standard error	*t*-value	*p*-value
Intercept	5112	2366	2.161	0.035
Implicit Affective Experience	2954	4848	0.609	0.545
Sleep Quality	-270	501	-0.540	0.592

Sleep Quality * Implicit Affective Experience	-490	1110	-0.441	0.661

Discussion

Summary of findings

Based on the results all three hypotheses can be rejected. There seems to be no significant correlation between implicit and explicit affective exercise experience. There is also no prediction strength on physical activity by implicit affective experience. And the relationship between physical activity and implicit affective experience is also not moderated by sleep.

No correlation between implicit and explicit

This research showed that there is inadequate evidence to show that there is a difference between explicit affective experiences and implicit affective experiences on the energy vs. tiredness dimension. This finding is in line with what Brand & Ekkekakis (2018) found. They found that implicit and explicit mechanisms in humans are not always in line with each other and researched it in combination with affective appraisals as well. However, their research combined all dimensions of the affective appraisals which explains that they found a small correlation between explicit and implicit affective appraisals whereas this research found none. On top of this, they used different methods than just an IAT to measure implicit affective appraisals. This results in a broader and more accurate view of the implicit system for affective appraisals.

Hakin (2013) researched whether the implicit and explicit mechanisms in the brain can reach the same result but in different routes. He assumed that the brain could by utilizing the ‘Yes It Can’ principle. He did find that the implicit mechanisms to solving a problem follow a different route, but it had a different solution than the explicit mechanisms. This can explain why the implicit and explicit affective experiences are also different from each other.

Generally, the explicit and implicit routes in the brain have different functions from each other (Dienes & Seth, 2010). Explicit processes are usually slow and deliberate, whereas implicit processes are fast and automatic (Evans, 2008). Explicit processes are inside our awareness whereas implicit is outside of awareness (Evans, 2008). This shows that the difference in implicit and explicit affective appraisals can be expected.

Implicit affective exercise as a predictor of physical activity

This research showed that implicit affective experience of people is not a significant predictor of physical activity. When someone implicitly associates physical activity with energy, they are not more likely to be physically active compared to a person who does not implicitly associate physical activity with energy. There is a lack of research into the role of implicit systems in relation to sports and physical activity in general. However, a recent study by Sjöros et al. (2024) showed that not feeling energized, whether implicitly or explicitly, does cause less physical activity and more sedentary behavior. The difference in results between Sjöros et al. (2024) and this study is that Sjöros et al. used an accelerometer to measure physical activity and constant self-report questionnaires to measure energy levels. This gives more accurate results on the variables of physical activity and perceived energy levels. Other research also shows that energy, or lack of it, plays an important role in the level of physical activity (Wender et al., 2022; Wennmann et al., 2015). This means energy does play a role in the level of physical activity.

None of the research mentioned above has explicitly focused on how the implicit association of energy levels can influence physical activity, and as shown by the first hypothesis, implicit and explicit may not always be on one line. Someone who implicitly associates physical activity with tiredness might still be physically active due to other reasons like motivation, or intention. The causation of someone being physically active is very complex and cannot be explained by just one variable (Bauman et al., 2012). Implicit affective exercise experience energy vs. tiredness does not seem to cause more physical activity on its own.

Moderation of sleep on the relation between affective exercise experience and physical activity

Based on the analysis of the results, sleep is not a moderating variable. There was no interaction effect for sleep quality on implicit affective experience and no significant main effect on physical activity. This is not in line with what other studies found (Holfeld & Ruthig, 2014). The study by Holfeld & Ruthig was done on older adults, a sample of over 600 participants and on a longitudal scale. This can explain why they found a predicting effect of sleep on physical activity and this study did not. It is also possible that in the sample used in this study, one or more other variables are more important in predicting physical activity.

Dishman et al. (2018) showed that motivation to be physically active plays a major role in predicting physical activity in students. Duda (2005) also showed that someone who is motivated is more driven to reach a goal and, therefore more likely to be physically active. It could also be a moderating variable. Someone who is motivated, but implicitly or explicitly associates physical activity with tiredness, is more likely to be physically active (Russell et al., 2018). The variable motivation can explain why there was no interaction effect. However, it is noticeable that sleep has no main effect since research indicates that sleep plays an important role in physical activity. People who have better sleep quality engage in more physical activity (Mead et al., 2019; Holfeld & Ruthig, 2014). Therefore, there should be a main effect observed when analyzing the relationship between sleep and physical activity.

Strengths and limitations

Limitations

The biggest limitation of this study was the SC-IATs. Over 35% of the participants had to be excluded because they did not reach the required number of correct links or were too slow too many times. The participants themselves had several comments about this. They said that the explanation of how the SC-IATs work went away too fast. This is due to the software we that was used. Therefore, they had no idea what to do which caused confusion and a lot of errors and misses. They also said that the words went away too fast, they sometimes could not even read the words and they were gone already. This caused many participants to miss too many words, resulting in an error in the output. Lastly, many participants said that they lost concentration since the SC-IAT was at the end of the questionnaire. This resulted in participants making too many mistakes or missing too many words. This caused them to be completely excluded from the sample. A recommendation that the participants had was that there should be a short practice round of about 10-20 words. They said that would cause them to get a feel for how it works which would result in fewer errors made by the participants.

Adding to this, research proves that an IAT does not always accurately measure the unconscious mindsets and attitudes (Schimmack, 2021). Blanton et al (2009) also showed that and IAT is also not always valid. This means that it might not measure what it is supposed to measure. Chevance et al., (2017) found that the SC-IAT is even less accurate and sensitive than a normal IAT when it is about physical activity and implicit attitudes. This means that a SC-IAT is worse at predicting physical activity levels based on implicit associations. Therefore, it cannot be said with certainty that the SC-IAT used in this research accurately measured the implicit associations towards physical activity. Using an IAT with two categories instead of a Single Category-IAT would give a more accurate picture of these implicit associations. Unfortunately, it was not possible in this research to use a regular IAT since it takes twice as long as a SC-IAT. Not utilizing an IAT could have resulted in not measuring implicit affective experiences but something else entirely.

Only 61 participants of the initial 250 were included in the analyses. This small sample size is partly due to that the questionnaire was very long. The length of the questionnaire caused many people to not fill out the questionnaire completely. This caused more than half of the people who started it to not even reach the end, causing them to be excluded completely. If the questionnaire was shorter, more people would have finished it, and the results would have been different. Ekkekakis et al., (2021) did similar research with 20 times as many participants and they did find a significant effect. To prove that implicit affective exercise has a small or moderate effect on physical activity, a big sample size is needed. Generally, to prove a small effect a sample of at least 500 people is needed (Serdar et al., 2021). Since this sample had only 61 participants, proving a small effect is unlikely

Strengths

Besides these limitations, the research also had strengths. It is difficult to measure what people unconsciously think. Usually, a more qualitative method is necessary to find out what people unconsciously think and feel. This study took a quantitative method to find out about the unconscious mindset and attitudes towards physical activity. This provides an easier way of collecting a bigger sample since it is easy to administer and convenient to spread around. Therefore, the sample size is bigger which is advantageous to the analysis

Another strength of this research is that it has never been done before. When doing the literature review about this topic, there was not one article that looked into the effect of the implicit affective exercise experience on physical activity. They all look at either environmental factors, intrinsic or extrinsic motivation or conscious self-report questionnaires (see Warburton, 2006). Doing research into something that has never been done before also inspires new ideas and perspectives to form for future research. This can lead to new explanations that could not have been found by existing forms of research.

Future research

This research investigated the effect of implicit tiredness or energy on physical activity. Physical activity is something that has been researched thoroughly, however, only research has been done on implicit attitudes toward sports, and whether they cause people to be physically active or not. Not much research is focused on the affective appraisals discussed by Ekkekakis et al. (2021). They measure affective appraisals towards physical activity on three core scales. This research has focused on the predicting strength of the implicit energy vs. tiredness scale. Future research could be done by combing the three scales and investigate their predicting strength combined. This could be done by having a cross-sectional sample that is larger than used in this research. This would have enough power to find a small or moderate effect of the affective appraisals. It would also make the results more generalizable to the greater population since this research mainly had students in the sample.

What might decrease the errors and misses in the IAT is using pictures instead of words. This also makes it easier to understand for people who are not confident in the English language. Foroni and Bel-Bahar (2010) found that utilizing pictures instead of words gives more valid and sensitive results in certain fields of research that use IATs. As Chevance et al. (2017) found, an IAT also more sensitive than an SC-IAT in measuring implicit attitudes toward physical activity. Therefore, for future research, using pictures and a normal IAT might be more fruitful in measuring the implicit affective associations towards physical activity.

Implications

This study found no correlation between implicit affective experiences and physical activity. This implicates that there are other variables at play for predicting physical activity.

It also implies that the other implicit affective appraisals might play a bigger role or that they all need to be combined in order to have a predicting effect.

Since sleep was found to not have a moderating effect, it implies that it might have a better predicting variable on its own, instead of a moderating role. Or that sleep does not play a role at all in predicting exercise behavior.

Lastly, since this is a new aspect of exercise psychology, this study found many new perspectives and initiatives of researching exercise behavior. This can result in findings in future research that can explain and predict exercise behavior more accurately than now.

Conclusion

All in all, this research found no significance of implicit affective experience of the energy vs tiredness dimension as a predictor variable of physical activity. It also found that implicit and explicit systems do not work the same. Since this research has focused on such a small part of the implicit affective exercise experience, more research is needed to find what role implicit affective exercise experience plays in predicting physical activity.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. *Neuropsychiatric disease and treatment, 3*(5), 553-567.

Alnawwar, M. A., Alraddadi, M. I., Algethmi, R. A., Salem, G. A., Salem, M. A., & Alharbi, A. A. (2023). The effect of physical activity on sleep quality and sleep disorder: systematic review. *Cureus*, *15*(8).

Ayalon, R. D., & Friedman Jr, F. (2008). The effect of sleep deprivation on fine motor coordination in obstetrics and gynecology residents. *American journal of obstetrics and gynecology, 199*(5), 576-e1.

Bauman, A. E., Reis, R. S., Sallis, J. F., Wells, J. C., Loos, R. J., & Martin, B. W. (2012). Correlates of physical activity: why are some people physically active and others not?. *The lancet*, *380*(9838), 258-271.

Bhandari, P. (2020, December 20). *What is effect size and why does it matter? (Examples)*. Scribbr. Retrieved June 22, 2024, https://www.scribbr.com/statistics/effect-size/

Blanton, H., Jaccard, J., Klick, J., Mellers, B., Mitchell, G., & Tetlock, P. E. (2009). Strong claims and weak evidence: reassessing the predictive validity of the IAT. *Journal of applied Psychology, 94*(3), 567.

Brand, R., & Ekkekakis, P. (2018). Affective–reflective theory of physical inactivity and exercise. *German Journal of exercise and sport research*, *48*(1), 48-58.

Brownstein, M., & Zalta, E. (2019). Implicit bias.

Chattu, V. K., Manzar, M. D., Kumary, S., Burman, D., Spence, D. W., & Pandi-Perumal, S.R. (2018, December). The global problem of insufficient sleep and its serious public health implications. In *Healthcare 7* (1), 1). MDPI.

Chevance, G., Héraud, N., Guerrieri, A., Rebar, A., & Boiché, J. (2017). Measuring implicit attitudes toward physical activity and sedentary behaviors: Test-retest reliability of three scoring algorithms of the Implicit Association Test and Single Category-Implicit Association Test. *Psychology of Sport and Exercise*, *31*, 70-78.

Chung, J., & Monroe, G. S. (2003). Exploring social desirability bias. *Journal of Business Ethics*, *44*, 291-302.

Craig, C., Marshall, A., Sjostrom, M., Bauman, A., Lee, P., Macfarlane, D., ... & Stewart, S. (2017). International physical activity questionnaire-short form. *J Am Coll Health*, *65*(7), 492-501.

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., ... & Oja, P. (2003). International physical activity questionnaire: 12-country reliability and validity. *Medicine & science in sports & exercise*, *35*(8), 1381-1395.

Dienes, Z., & Seth, A. (2010). The conscious and the unconscious. *Encyclopedia of behavioral neuroscience*, *1*, 322-327.

Dishman, R. K., McIver, K. L., Dowda, M., & Pate, R. R. (2018). Declining physical activity and motivation from middle school to high school. *Medicine and science in sports and exercise*, *50*(6), 1206.

Duda, J. L. (2005). Motivation in sport. *A handbook of competence and motivation*, *318*, 335.

Durmer, J. S., & Dinges, D. F. (2005, March). Neurocognitive consequences of sleep deprivation. In *Seminars in neurology (25* (01), 117-129). Thieme Medical Publishers

Ekkekakis, P., Zenko, Z., & Vazou, S. (2021). Do you find exercise pleasant or unpleasant?

Evans, J. S. B. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol.*, *59*, 255-278.

Famodu, O. A., Barr, M. L., Holásková, I., Zhou, W., Morrell, J. S., Colby, S. E., & Olfert, M. D. (2018). Shortening of the Pittsburgh Sleep Quality Index survey using factor analysis. *Sleep disorders*, *2018*.

Forde, C. (2018). Scoring the international physical activity questionnaire (IPAQ). *University of Dublin*, *3*.

Foroni, F., & Bel-Bahar, T. (2010). Picture-IAT versus Word-IAT: level of stimulus representation influences on the IAT. *European Journal of Social Psychology*, *40*(2), 321-337.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology*, *74*(6), 1464.

Hagger, M. S. (2016). Non-conscious processes and dual-process theories in health Psychology. *Health Psychology Review*, *10*(4), 375-380.

Hassin, R. R. (2013). Yes it can: On the functional abilities of the human unconscious. *Perspectives on Psychological Science*, *8*(2), 195-207.

Holfeld, B., & Ruthig, J. C. (2014). A longitudinal examination of sleep quality and physical activity in older adults. *Journal of Applied Gerontology, 33*(7), 791-807.

inadequate sleep on health and public safety drive an explosion of sleep

Karpinski, A., & Steinman, R. B. (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of personality and social psychology*, *91*(1), 16.

Kredlow, M. A., Capozzoli, M. C., Hearon, B. A., Calkins, A. W., & Otto, M. W. (2015). The effects of physical activity on sleep: a meta-analytic review. *Journal of behavioral medicine, 38*, 427-449.

Lee, P. H., Macfarlane, D. J., Lam, T. H., & Stewart, S. M. (2011). Validity of the international physical activity questionnaire short form (IPAQ-SF): A systematic review. *International journal of behavioral nutrition and physical activity*, *8*, 1-11.

Mead, M. P., Baron, K., Sorby, M., & Irish, L. A. (2019). Daily associations between sleep and physical activity. *International journal of behavioral medicine, 26*, 562-568.

Mavrić, F., Kahrović, I., Murić, B., & Radenković, O. (2014). The effects of regular physical exercise on the human body. *Fizička kultura*, *68*(1), 29-38.

Ohayon, M., Wickwire, E. M., Hirshkowitz, M., Albert, S. M., Avidan, A., Daly, F. J., ... & Vitiello, M. V. (2017). National Sleep Foundation's sleep quality recommendations: first report. *Sleep health*, *3*(1), 6-19.

research. *Pharmacy and Therapeutics*, *43*(12), 758.

Russell, S., Jenkins, D., Rynne, S., Halson, S. L., & Kelly, V. (2019). What is mental fatigue in elite sport? Perceptions from athletes and staff. *European journal of sport science*, *19*(10), 1367-1376.

Schimmack, U. (2021). The Implicit Association Test: A method in search of a construct. *Perspectives on Psychological Science*, *16*(2), 396-414.

Serdar, C. C., Cihan, M., Yücel, D., & Serdar, M. A. (2021). Sample size, power and effect size revisited: simplified and practical approaches in pre-clinical, clinical and laboratory studies. *Biochemia medica*, *31*(1), 27-53.

Shahid, A., Wilkinson, K., Marcu, S., & Shapiro, C. M. (2012). Pittsburgh sleep quality index (PSQI). *STOP, THAT and One Hundred Other Sleep Scales*, 279-283.

Sjöros, T., Norha, J., Johansson, R., Laine, S., Garthwaite, T., Vähä-Ypyä, H., ... & Heinonen, I. H. (2024). Tiredness after work associates with less leisure-time physical activity. *Scientific Reports*, *14*(1), 7965.

Strobach, T., Englert, C., Jekauc, D., & Pfeffer, I. (2020). Predicting adoption and maintenance of physical activity in the context of dual-process theories. *Performance Enhancement & Health*, *8*(1), 100162.

The Affective Exercise Experiences (AFFEXX) questionnaire. *Psychology of Sport and Exercise*, *55*, 101930.

Van der Heijden, K. B., Vermeulen, M. C., Donjacour, C. E., Gordijn, M. C., Hamburger, H. L., Meijer, A. M., ... & Weysen, T. (2018). Chronic sleep reduction is associated with academic achievement and study concentration in higher education students. *Journalof Sleep Research*, *27*(2), 165-174.

Warburton, D. E., Nicol, C. W., & Bredin, S. S. (2006). Health benefits of physical activity: the evidence. *Cmaj*, *174*(6), 801-809.

Wender, C. L., Manninen, M., & O’Connor, P. J. (2022). The effect of chronic exercise on energy and fatigue states: A systematic review and meta-analysis of randomized trials. *Frontiers in psychology*, *13*, 907637.

Wennman, H., Kronholm, E., Partonen, T., Peltonen, M., Vasankari, T., & Borodulin, K. (2015). Evening typology and morning tiredness associates with low leisure time physical activity and high sitting. *Chronobiology international*, *32*(8), 1090-1100.

World Health Organization: WHO. (2022, October 5). *Physical activity*. https://www.who.int/news-room/fact-sheets/detail/physical-activity

Worley, S. L. (2018). The extraordinary importance of sleep: the detrimental effects of

Appendix

Appendix A

Informed Consent Form

What are the intentions of this study?
You are invited to take part in a research study that aims to investigate the relationship between conscious and unconscious emotions towards Physical activity, with the ultimate goal to transform negative associations towards activity in more positive ones.

What does this study look like?
In this first part, you will be asked to fill in a questionnaire. After filling it in, there will be a field to leave your e-mail adress. It is important to note that this e-mail address is only going to be used to invite you to the second part of the study, which will consist of an Implicit Association Test. Afterwards, your e-mail address will be deleted from the dataset.

Can I also take part in this study?
If you are 18 years or older, and have sufficient skills in the English language (e.g. reading a text fluently and understanding most of the terms), you are suitable to take part in this study.

Do I need to take part?
No. Participation in this study is voluntary, and you have the right to withdraw at any time without any consequences. If you decide to withdraw, your data will not be used in the study, and any information collected till that point will be discarded.

What will happen when I agree to take part in this study?
When you decide to take part in this study, you will automatically be redirected to the questionnaire, which will take around 20 minutes. In this questionnaire, none of the answers are right or wrong, and we are only interested in your own experiences/opinions.

What are the risks of taking part in this study?
During this research, you will answer questions about yourself, and about experiences that you had with exercise in the past. If at some part you might struggle with possible traumas or other factors detrimental to health, feel free to inform one of the following links:
- https://www.113.nl/ or https://www.slachtofferhulp.nl/ (Dutch)
- https://www.hilfe-info.de (German)
- https://www.mind.org.uk/information-support/types-of-mental-health-problems/trauma/useful-contacts/ (English)

After the data collection, what is going to happen with my results?
For the data analysis, no identifiable information will be used, and every possible thing that could link you to the answers is going to be anonymized. The collected data will be stored on a highly encrypted device which are only accessible for us and our supervisor.

If I have any other questions, whom can I contact then?
The research team for this questionnaire is always open to answering questions, and they are reachable by the following email adresses:
- G.R. Bekhuis (g.r.bekhuis@student.utwente.nl)

- A.M. van den Berg (a.m.vandenberg-1@student.utwente.nl)
- G.S. van Beveren (g.s.vanbeveren@student.utwente.nl)
- A.M. Freiberg (a.m.freiberg@student.utwente.nl'
- L.C. Hessels (l.c.hessels@student.utwente.nl)
- G.P. Kaczmarek (g.p.kaczmarek@student.utwente.nl)
- T. Zandstra (t.zandstra@student.utwente.nl)

Who are the supervisors of the project?
The two supervisors for this project are:
- A. Braakman-Jansen (l.m.a.braakman-jansen@utwente.nl)
- M.E. Pieterse (m.e.pieterse@utwente.nl)

Appendix B

Normality graphs of the different variables

Figure B1

Normal graph implicit affective exercise

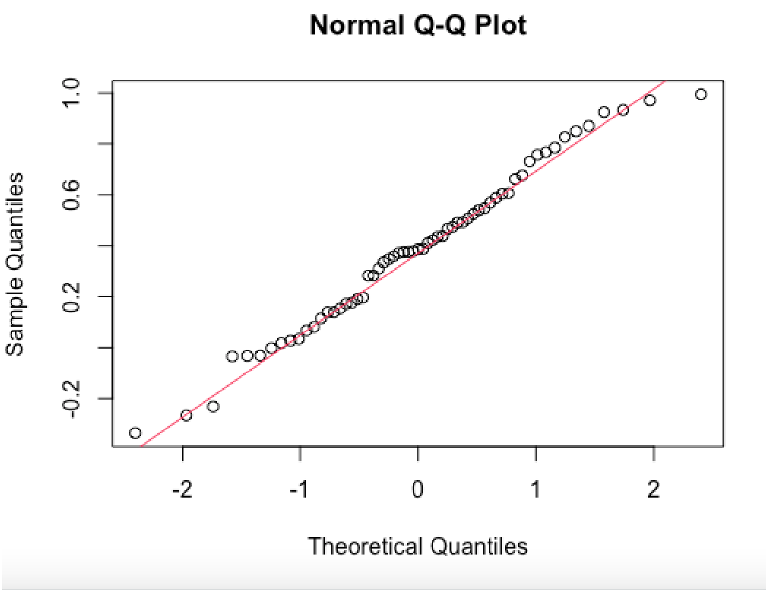


Figure B2

Normal graph explicit affective exercise

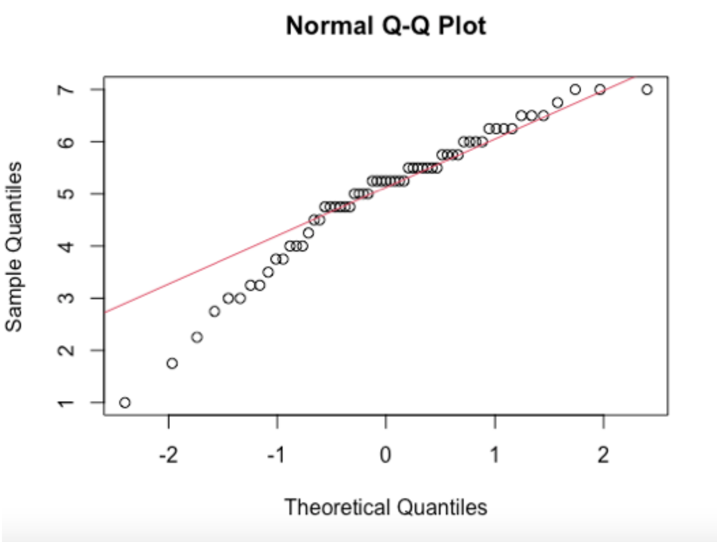


Figure B3

Normal graph physical activity

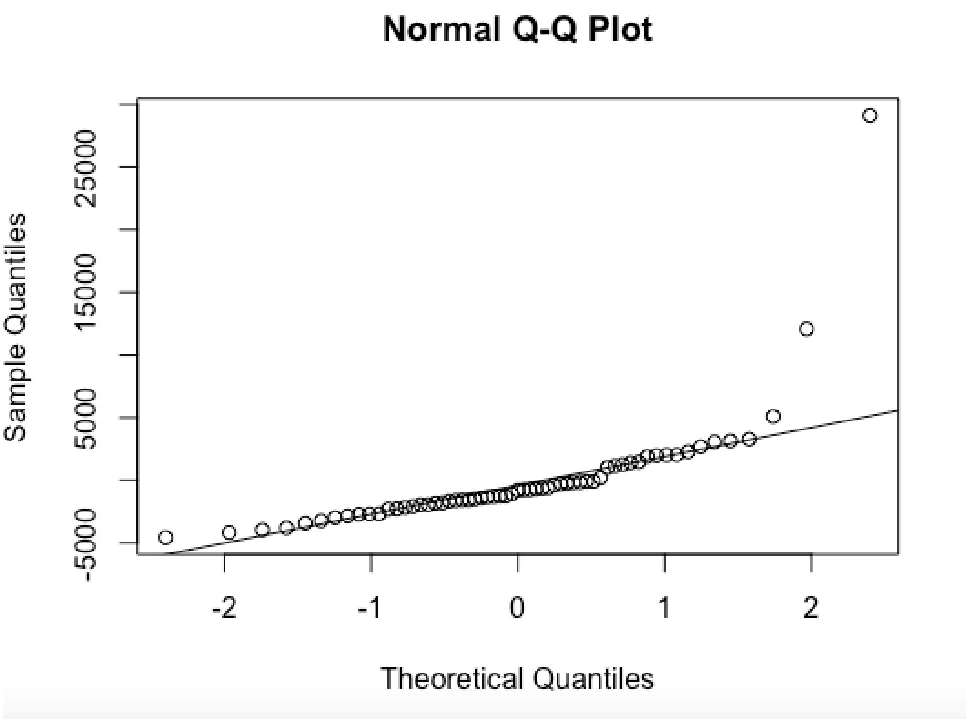
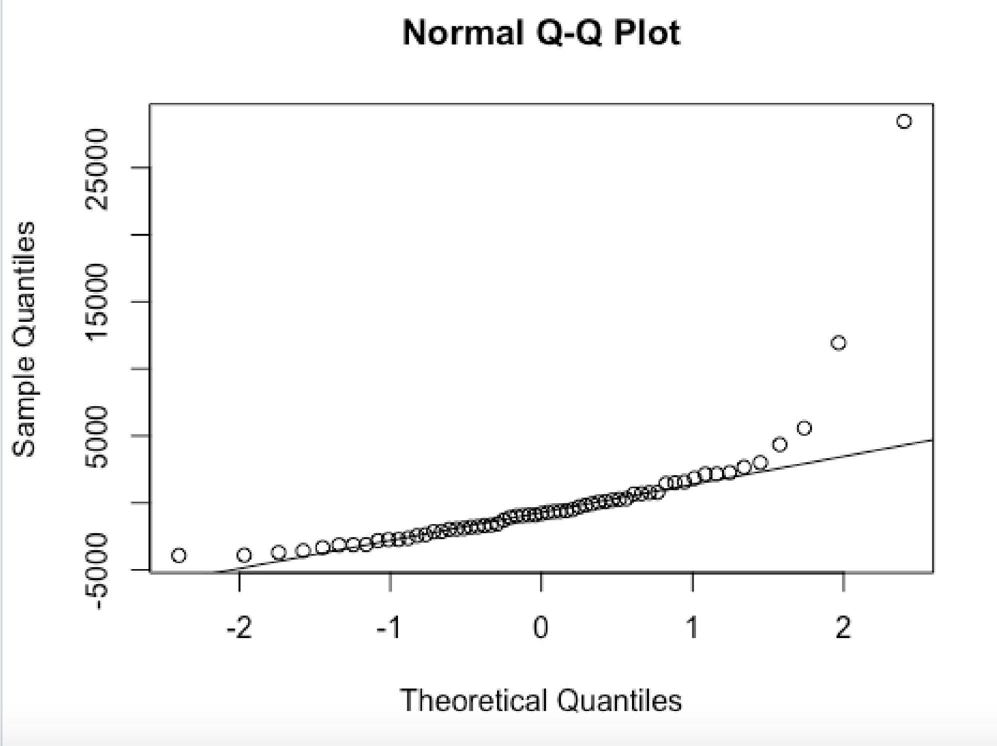


Figure B4

Normal graph sleep quality



Appendix C

Assumptions of the Second Hypothesis

Figure C1

Homoscedasticity of the residuals

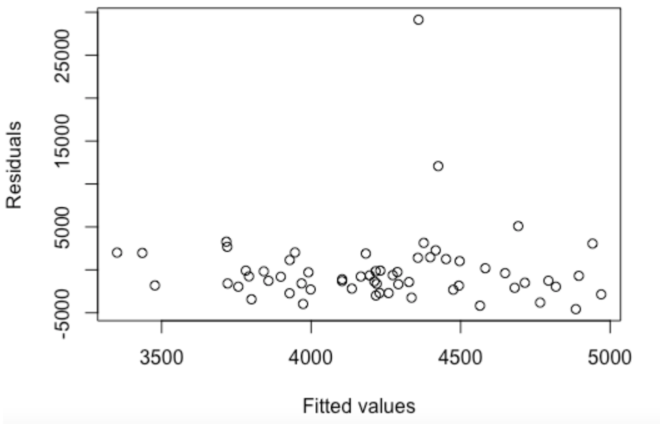
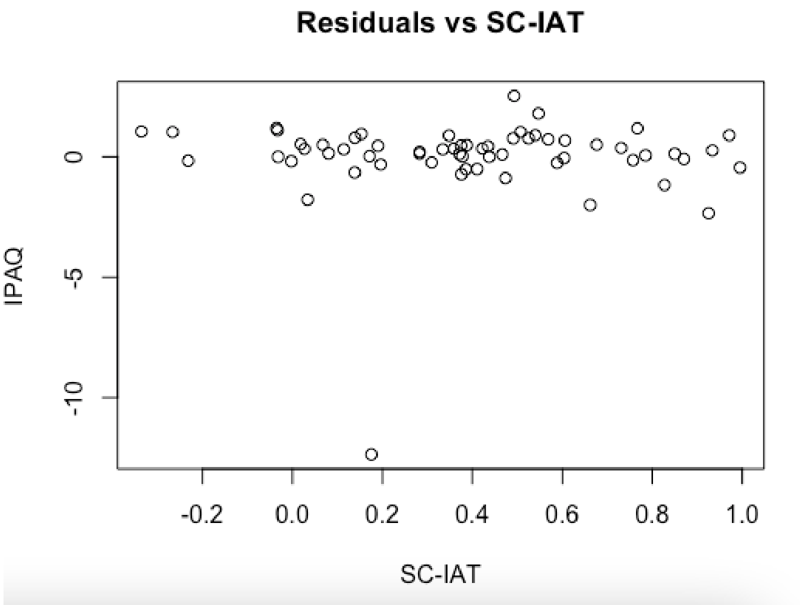


Figure C2

Linearity of the variables



Appendix D

Assumptions of the Third Hypothesis

Figure D1

Homoscedasticity of the residuals

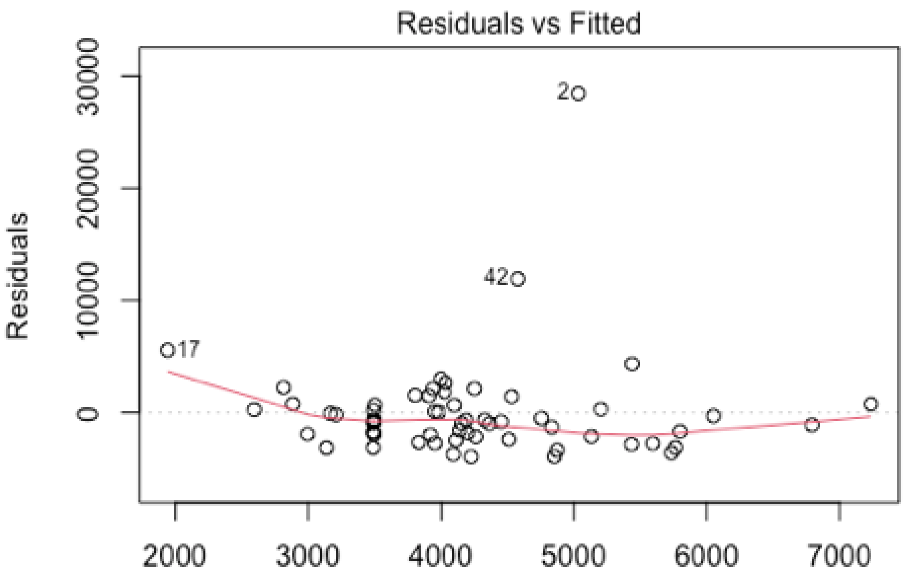
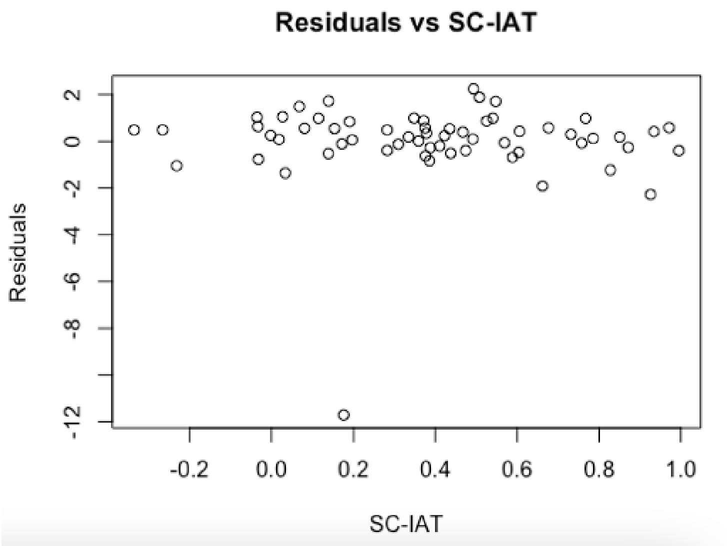


Figure D2

Linearity of the variables



Appendix E

Acknowledgement of Usage of AI

During the preparation of this work, I used Grammarly to correct my misspelled words and get suggestions to improve my sentence structure. After using this tool, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

During the preparation of this work, I also used ChatGPT to help me find appropriate code for the analysis in R. After using this service, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

Appendix F

Code Used for this Thesis

```
rm(list = ls())


# load packages
library(dplyr)    # For data manipulation
library(ggplot2)  # For data visualization
library(tidyr)    # For data tidying
library(readr)    # For reading data
library(lubridate)# For working with dates
library(stringr)  # For string manipulation
install.packages("readx1")
# Load the readxl package
library(readxl)


excel_file <- "/Users/twanzandstra/Desktop/R Data/data 1.xlsx"


# Read the specific sheet named "data1" into R
data <- read_excel ("/Users/twanzandstra/Desktop/R Data/data 1.xlsx")


View(data)


#cleaned data
vars_to_keep <- c("C101_01", "C104", "C105", "C106", "C106_03", "C110", "C111",
"C112", "D102_02", "D103_01", "D103_02",
```

```
            "D106_01", "D107_01", "D107_02", "D109_01", "D110_01", "D110_02",
"F408", "F409", "E102_12", "E102_13",
            "E102_18", "E102_20", "F401", "F402", "F403", "F404", "F405_02_1",
"F405_02_2", "F405_02_3", "F405_02_4",
            "F405_03_1", "F405_03_2", "F405_03_3", "F405_03_4", "F405_04_1",
"F405_04_2", "F405_04_3", "F405_04_4",
            "F405_05_1", "F405_05_2", "F405_05_3", "F405_05_4", "F405_06_1",
"F405_06_2", "F405_06_3", "F405_06_4",
            "F405_07_1", "F405_07_2", "F405_07_3", "F405_07_4", "F405_08_1",
"F405_08_2", "F405_08_3", "F405_08_4",
            "F405_09_1", "F405_09_2", "F405_09_3", "F405_09_4", "F405_10_1",
"F405_10_2", "F405_10_3", "F405_10_4", "F408", "F409",
            "F601_01", "F601_02", "F601_03", "F601_04", "F601_05", "F601_06",
"F601_07", "F601_08", "F601_09", "F601_10",
            "F601_11", "F601_12", "F601_13", "F601_14", "F601_15", "F601_16",
"F601_17", "F601_18", "F601_19", "F601_20",
            "F601_21", "F601_22", "F601_23", "F601_24", "F601_25", "F601_26",
"F601_27", "F601_28", "G101i0", "G101xD",
            "G101xD1", "G101xD2", "G101xD3", "G101nT1", "G101nT2", "G101nT3",
"G101nT4", "G101nX1", "G101nX2", "G101nX3",
            "G101nX4", "G101nN1", "G101nN2", "G101nN3", "G101nN4", "G101nE1",
"G101nE2", "G101nE3", "G101nE4", "G101mL1",
            "G101mL2", "G101mL3", "G101mL4", "TIME_SUM")

data_clean <- data[, vars_to_keep]
```

```
View(data_clean)

#clean data set
variables_to_exclude <- c("C101_01", "C104", "C105", "C106", "C106_03", "C107_01",
"C110", "C111", "C112,")

# Create a new dataset without the variables to exclude
data_subset <- data_clean[, !names(data_clean) %in% variables_to_exclude]

View(data_subset)

#delete varaibles
variables_to_delete <- c("F405_02_CN", "F405_03_CN", "F405_04_CN",
"F405_05_CN", "F405_06_CN", "F405_07_CN", "F405_08_CN", "F405_09_CN",
"F405_10_CN")

data_subset <- data_subset[, !(names(data_subset) %in% variables_to_delete)]

#completely clean data set is data_subset

# make a copy

data_subset2 <- data_subset
```

```
# make data_subset3 numerical

numeric_cols <- sapply(data_subset2, is.numeric)

print(numeric_cols)


data_subset2[] <- lapply(data_subset3, as.numeric)


#data_subset3 is numeric


# Delete the first row

data_subset2 <- data_subset2[-1, ]


#IPAQ code

# List of variables to consider

variables_to_check <- c("D103_02", "D107_02", "D110_02")


# Remove values greater than or equal to 60 in specified variables

data_subset2[, variables_to_check][data_subset2[, variables_to_check] >= 60] <- NA


#remove c112 (living area from data_subset3)

data_subset2 <- data_subset2[, !names(data_subset2) %in% "C112"]


#make a back-up copy of data_subset2


data_subset3 <- data_subset2
```

```
# formula to make IPAQ variable
#Replace NA with 0 for specified variables
data_subset2$D102_02[is.na(data_subset2$D102_02)] <- 0
data_subset2$D103_01[is.na(data_subset2$D103_01)] <- 0
data_subset2$D103_02[is.na(data_subset2$D103_02)] <- 0
data_subset2$D106_01[is.na(data_subset2$D106_01)] <- 0
data_subset2$D107_01[is.na(data_subset2$D107_01)] <- 0
data_subset2$D107_02[is.na(data_subset2$D107_02)] <- 0
data_subset2$D109_01[is.na(data_subset2$D109_01)] <- 0
data_subset2$D110_01[is.na(data_subset2$D110_01)] <- 0
data_subset2$D110_02[is.na(data_subset2$D110_02)] <- 0

data_subset2$IPAQ <- with(data_subset2, {
  result <- D102_02 * ((D103_01 * 60 + D103_02) * 8) +
    D106_01 * ((D107_01 * 60 + D107_02) * 4) +
    D109_01 * ((D110_01 * 60 + D110_02) * 3.3)
  return(result)
})

#AFFEXX code
# Calculate the average of the scores and round to two decimal places
data_subset2$AFFEXX <- round(rowMeans(data_subset2[c("E102_12", "E102_13",
"E102_18", "E102_20")]), 2)

#Copy of data_subset4 before IAT specifics were deleted
```

```
data_subset2backup <-data_subset2

# exclude IAT specifics
# Exclude specified variables from data_subset4
data_subset2 <- data_subset2[, !colnames(data_subset2) %in% c("G101nT1",
"G101nT2", "G101nT3", "G101nT4",
                                       "G101nX1", "G101nX2", "G101nX3",
"G101nX4",
                                       "G101nN1", "G101nN2", "G101nN3",
"G101nN4",
                                       "G101nE1", "G101nE2", "G101nE3", "G101nE4",
                                       "G101mL1", "G101mL2", "G101mL3",
"G101mL4")]


# PSQI questionnaire
# exclude variables mostly SQS and two Matrix
# delete the SQS
data_subset2 <- data_subset2[, !colnames(data_subset2) %in% c("F601_01", "F601_02",
"F601_03", "F601_04", "F601_05", "F601_06", "F601_07", "F601_08", "F601_09",
"F601_10", "F601_11", "F601_12", "F601_13", "F601_14", "F601_15", "F601_16",
"F601_17", "F601_18", "F601_19", "F601_20", "F601_21", "F601_22", "F601_23",
"F601_24", "F601_25", "F601_26", "F601_27", "F601_28")]
```

```
#Delete matrix
data_subset2 <- data_subset2[, !colnames(data_subset2) %in% c("F405_04_1",
"F405_04_02", "F405_04_3", "F405_04_4", "F405_07_1", "F405_07_2", "F405_07_3" ,
"F405_07_4")]

View(data_subset2)

#make a copy of dataset
data_subset3 <-data_subset2
rm(data_subset3)
rm(data_subset2)
data_subset4 <-data_subset3
rm(data_subset4)
data_subset5 <-data_subset4
rm(data_subset5)
data_subset6 <-data_subset5
rm(data_subset6)
data_subset7 <-data_subset6
rm(data_subset7)
data_subset8 <-data_subset7
rm(data_subset8)
data_subset9 <-data_subset8
rm(data_subset9)
data_subset10 <-data_subset9
rm(data_subset10)
```

```
data_subset2 <- data_subset10

data_subset3 <- data_subset2

#delete all participants that had two or more answers in any matrix question
# variable 02
rows_to_delete <- which(rowSums(data_subset2[, c("F405_02_1", "F405_02_2",
"F405_02_3", "F405_02_4")] == 2) > 1)

data_subset2 <- data_subset2[-rows_to_delete, ]

#variable 03 ## no double

# variable 05
rows_to_delete5 <- which(rowSums(data_subset2[, c("F405_05_1", "F405_05_2",
"F405_05_3", "F405_05_4")] == 2) > 1)

data_subset2 <- data_subset2[-rows_to_delete5, ]

#variable 06
rows_to_delete2 <- which(rowSums(data_subset2[, c("F405_06_1", "F405_06_2",
"F405_06_3", "F405_06_4")] == 2) > 1)

data_subset2 <- data_subset2[-rows_to_delete2, ]
```

```
#variable 08 ## no double
rows_to_delete3 <- which(rowSums(data_subset9[, c("F405_08_1", "F405_08_2",
"F405_08_3", "F405_08_4")] == 2) > 1)

data_subset9 <- data_subset9[-rows_to_delete3, ]

#variable 09 ## no double
rows_to_delete6 <- which(rowSums(data_subset10[, c("F405_09_1", "F405_09_2",
"F405_09_3", "F405_09_4")] == 2) > 1)

data_subset10 <- data_subset10[-rows_to_delete6, ]

#Variable 10
rows_to_delete7 <- which(rowSums(data_subset2[, c("F405_10_1", "F405_10_2",
"F405_10_3", "F405_10_4")] == 2) > 1)

data_subset2 <- data_subset2[-rows_to_delete7, ]

## data_subset2 is the filtered data subset
data_subset3 <- data_subset2
rm(data_subset2)
data_subset4 <- data_subset3



# remove the F408 and F409 duplicate
```

```
data_subset3 <- data_subset3[, -10]


data_subset3 <- data_subset3[, -10]


# change all 1 into NA
# Variables to modify
vars_to_modify <- c("F405_02_1", "F405_02_2", "F405_02_3", "F405_02_4",
                    "F405_03_1", "F405_03_2", "F405_03_3", "F405_03_4",
                    "F405_05_1", "F405_05_2", "F405_05_3", "F405_05_4",
                    "F405_06_1", "F405_06_2", "F405_06_3", "F405_06_4",
                    "F405_08_1", "F405_08_2", "F405_08_3", "F405_08_4",
                    "F405_09_1", "F405_09_2", "F405_09_3", "F405_09_4",
                    "F405_10_1", "F405_10_2", "F405_10_3", "F405_10_4")


# Loop through each variable and replace 1 with NA
for(var in vars_to_modify) {
  data_subset3[[var]][data_subset3[[var]] == 1] <- NA
}


## copy
data_subset4 <- data_subset3
rm(data_subset3)
data_subset5 <- data_subset4
rm(data_subset4)
data_subset6 <- data_subset5
```

```r
data_subset7 <- data_subset6
rm(data_subset6)
data_subset8 <- data_subset7
rm(data_subset7)
data_subset9 <- data_subset8

## variable 02
#assign scores to the variables
# Define variables to modify
vars_to_modify <- c("F405_02_1", "F405_02_2", "F405_02_3", "F405_02_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_02 <- rowSums(data_subset8[, c("F405_02_1", "F405_02_2",
"F405_02_3", "F405_02_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
```

```
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_02_1",
"F405_02_2", "F405_02_3", "F405_02_4"))]

## variable 03
# Define variables to modify
vars_to_modify3 <- c("F405_03_1", "F405_03_2", "F405_03_3", "F405_03_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify3) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify3) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_03 <- rowSums(data_subset8[, c("F405_03_1", "F405_03_2",
"F405_03_3", "F405_03_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_03_1",
"F405_03_2", "F405_03_3", "F405_03_4"))]

## variable 05
# Define variables to modify
vars_to_modify4 <- c("F405_05_1", "F405_05_2", "F405_05_3", "F405_05_4")
```

```
# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify4) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify4) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_05 <- rowSums(data_subset8[, c("F405_05_1", "F405_05_2",
"F405_05_3", "F405_05_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_05_1",
"F405_05_2", "F405_05_3", "F405_05_4"))]

## variable 06
# Define variables to modify
vars_to_modify5 <- c("F405_06_1", "F405_06_2", "F405_06_3", "F405_06_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify5) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify5) - 1
}
```

```
# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_06 <- rowSums(data_subset8[, c("F405_06_1", "F405_06_2",
"F405_06_3", "F405_06_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_06_1",
"F405_06_2", "F405_06_3", "F405_06_4"))]

## variable 08
# Define variables to modify
vars_to_modify6 <- c("F405_08_1", "F405_08_2", "F405_08_3", "F405_08_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify6) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify6) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_08 <- rowSums(data_subset8[, c("F405_08_1", "F405_08_2",
"F405_08_3", "F405_08_4")], na.rm = TRUE)
```

```
# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_08_1",
"F405_08_2", "F405_08_3", "F405_08_4"))]

## variable 09
# Define variables to modify
vars_to_modify7 <- c("F405_09_1", "F405_09_2", "F405_09_3", "F405_09_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify7) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify7) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_09 <- rowSums(data_subset8[, c("F405_09_1", "F405_09_2",
"F405_09_3", "F405_09_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_09_1",
"F405_09_2", "F405_09_3", "F405_09_4"))]

## variable 10
# Define variables to modify
```

```
vars_to_modify8 <- c("F405_10_1", "F405_10_2", "F405_10_3", "F405_10_4")

# Loop through each variable and replace 2 with its corresponding value
for (var_name in vars_to_modify8) {
  data_subset8[[var_name]][data_subset8[[var_name]] == 2] <- match(var_name,
vars_to_modify8) - 1
}

# add rows together
# Create a new variable F405_02 by summing the values of F405_02_1 to F405_02_4
data_subset8$F405_10 <- rowSums(data_subset8[, c("F405_10_1", "F405_10_2",
"F405_10_3", "F405_10_4")], na.rm = TRUE)

# Remove the individual variables from the dataset
data_subset8 <- data_subset8[, !(names(data_subset8) %in% c("F405_10_1",
"F405_10_2", "F405_10_3", "F405_10_4"))]

### total score of this component, add up all variables and check scoring key
data_subset8$sum_F405 <- rowSums(data_subset8[, c("F405_03", "F405_05",
"F405_06", "F405_08", "F405_09", "F405_10")], na.rm = TRUE)

data_subset8 <- subset(data_subset8, select = -c(F405_03, F405_05, F405_06, F405_08,
F405_09, F405_10))

# give the score from score key
```

```
### total score of this component, add up all variables and check scoring key
data_subset8$sum_F405 <- rowSums(data_subset8[, c("F405_03", "F405_05",
"F405_06", "F405_08", "F405_09", "F405_10")], na.rm = TRUE)

data_subset8 <- subset(data_subset8, select = -c(F405_03, F405_05, F405_06, F405_08,
F405_09, F405_10))

# give the score from score key
# Recode sum_F405 variable
data_subset8$sum_F405_score <- ifelse(data_subset8$sum_F405 == 0, 0,
                                      cut(data_subset8$sum_F405,
                                          breaks = c(0, 6, 12, Inf),
                                          labels = c(1, 2, 3),
                                          right = FALSE))
# delete sum_f405
data_subset8$sum_F405 <- NULL


# F408 and F409 scoring
# Convert scores for F408 and F409
data_subset8$F408 <- ifelse(data_subset8$F408 == 1, 0,
                            ifelse(data_subset8$F408 == 2, 1,
                                   ifelse(data_subset8$F408 == 3, 2,
                                          ifelse(data_subset8$F408 == 4, 3, NA))))
```

```
data_subset8$F409 <- ifelse(data_subset8$F409 == 1, 0,
                     ifelse(data_subset8$F409 == 2, 1,
                        ifelse(data_subset8$F409 == 3, 2,
                           ifelse(data_subset8$F409 == 4, 3, NA))))

# Sum up F408 and F409, handling NA values
data_subset8$SumF408_9 <- rowSums(data_subset8[, c("F408", "F409")], na.rm =
TRUE)

data_subset8 <- subset(data_subset8, select = -c(F408, F409))

## delete AFFEXX and IPAQ variables from the data set
data_subset8 <- subset(data_subset8, select = -c(D102_02, D103_01, D103_02,
D106_01, D107_01, D107_02, D109_01, D110_01, D110_02, E102_12, E102_13,
E102_18, E102_20))

## F404
data_subset8$F404_score <- ifelse(data_subset8$F404 %in% c(5, 6, 7, 8), 0,
                         ifelse(data_subset8$F404 == 4, 1,
                            ifelse(data_subset8$F404 == 3, 2, 3)))
data_subset8 <- subset(data_subset8, select = -F404)

## F402
data_subset8$F402_score <- ifelse(data_subset8$F402 %in% c(1, 2), 0,
```

```
                        ifelse(data_subset8$F402 == 3, 1,
                            ifelse(data_subset8$F402 == 4, 2,
                                ifelse(data_subset8$F402 == 5, 3, NA))))

data_subset8 <- subset(data_subset8, select = -c(F401, F402, F403))

# add scores F402 and F405_02
# Calculate the sum of F402 and F405_02
data_subset8$sum_F402_F405_02 <- data_subset8$F402_score + data_subset8$F405_02

# Assign points based on the sum
data_subset8$new_variable <- ifelse(data_subset8$sum_F402_F405_02 %in% 0, 0,
                          ifelse(data_subset8$sum_F402_F405_02 %in% 1:2, 1,
                              ifelse(data_subset8$sum_F402_F405_02 %in% 3:4, 2,
                                  ifelse(data_subset8$sum_F402_F405_02 %in% 5:6, 3,
NA))))


# Delete specified variables
data_subset8 <- subset(data_subset8, select = -c(F402_score, F405_02,
sum_F402_F405_02))

names(data_subset8)[names(data_subset8) == "new_variable"] <-
"score_F402_F405_02"
```

```
#copy final data set
data_subset9 <- data_subset8



## Final score of the PSQI
data_subset8$PSQI <- rowSums(data_subset8[, c("sum_F405_score", "SumF408_9",
"F404_score", "score_F402_F405_02")], na.rm = TRUE)

data_subset8 <- subset(data_subset8, select = -c(sum_F405_score, SumF408_9,
F404_score, score_F402_F405_02))

data_subset9 <- data_subset8

## research question 1
#delete columns that are not needed
data_subset8 <- subset(data_subset8, select = -c(G101i0, G101xD1, G101xD2, G101xD3,
TIME_SUM))
data_subset8 <- subset(data_subset8, select = -c(G101i0))

#delete the -9.00000 in Sc-IAT
data_subset8 <- data_subset8[data_subset8$G101xD >= -1 & data_subset8$G101xD <=
1, ]

data_subset10 <- data_subset8
```

```
# Rename variable
names(data_subset8)[names(data_subset8) == "G101xD"] <- "SC_IAT"


## test normality
# Load necessary packages
library(psych)


# Assuming your data is stored in a data frame called data_subset8


# 1. Normality of Variables
# Assuming AFFEXX and SC-IAT are the variables of interest
shapiro.test(data_subset8$AFFEXX)  # Shapiro-Wilk test for AFFEXX
shapiro.test(data_subset8$SC_IAT)  # Shapiro-Wilk test for SC-IAT


# Assuming your variable of interest is stored in a vector called "x"
x <- data_subset8$AFFEXX  # Replace "AFFEXX" with the name of your variable
y <- data_subset8$SC_IAT
# Create QQ plot
qqnorm(x)
qqline(x, col = 2)  # Add a reference line


qqnorm(y)
qqline(y, col = 2)


# 2. Bivariate parametric Correlation
```

```
correlation <- cor.test(data_subset8$AFFEXX, data_subset8$SC_IAT, method = "spearman")
correlation

## hypothesis 2
# Load necessary libraries
install.packages("lmtest")
library(lmtest) # For Breusch-Pagan test for homoscedasticity
library(ggplot2) # For visualization

# Fit the linear regression model
model <- lm(IPAQ ~ SC_IAT, data = data_subset8)

# Check assumptions

## 1. Normality of residuals
shapiro.test(residuals(model)) # Shapiro-Wilk test for normality
qqnorm(residuals(model)) # QQ plot
qqline(residuals(model)) # Add a reference line to the QQ plot

## 2. Homoscedasticity of residuals (constant variance)
plot(model$fitted.values, model$residuals, xlab = "Fitted values", ylab = "Residuals") # Breusch-Pagan test
```

```
# Install and load the lmtest package if you haven't already
install.packages("lmtest")
library(lmtest)

# Fit a linear regression model
model <- lm(IPAQ ~ SC_IAT, data = data_subset8)
## log transformation of IPAQ to get linearity
model <- lm(log(IPAQ) ~ SC_IAT, data = data_subset8)
data_subset8$IPAQ[data_subset8$IPAQ == 0.0] <- 0.01



# Perform Breusch-Pagan test for heteroscedasticity
bp_test <- bptest(model)
bp_test

## 3. Linearity (relationship between predictors and response)
plot(data_subset8$SC_IAT, residuals(model), xlab = "SC-IAT", ylab = "IPAQ", main =
"Residuals vs SC-IAT") # Scatterplot of residuals vs SC-IAT

## 4. Multicollinearity (between predictors)
vif(model) # Variance Inflation Factor (VIF)

## 5. Independence (of errors)
dwtest(model) # Durbin-Watson test
```

```
# Summary of the regression model
summary(model)

# Diagnostic plots
plot(model)

# Assuming data_subset9 contains the IPAQ and SC-IAT variables
correlation <- cor.test(data_subset8$IPAQ, data_subset8$SC_IAT, method = "spearman")
print(correlation)

## hypothesis 3
# Load necessary libraries
library(ggplot2)  # For visualization
library(dplyr)    # For data manipulation

# Create a scatterplot of SC_IAT scores
plot(data_subset8$SC_IAT, main = "Scatterplot of SC_IAT Scores", xlab = "SC_IAT
Scores", ylab = "Frequency")
# Create a scatterplot of SC_IAT scores with customized axis labels
plot(data_subset8$SC_IAT, main = "Scatterplot of SC_IAT Scores", xlab = "", ylab =
"Scores")


# Check assumptions
# Fit the linear regression model with interaction term
```

```
model <- lm(IPAQ ~ SC_IAT * PSQI, data = data_subset8)

# Check assumptions
# 1. Normality of residuals
shapiro.test(residuals(model))  # Shapiro-Wilk test for normality
qqnorm(residuals(model))  # Q-Q plot
qqline(residuals(model))  # Add reference line to Q-Q plot

# 2. Homoscedasticity of residuals (constant variance)
plot(model$fitted.values, model$residuals, xlab = "Fitted values", ylab = "Residuals")  # Plot of residuals vs fitted values
plot(model, which = 1)

bp_test <- bptest(model)
bp_test

# 3. Linearity (relationship between predictors and response)
model <- lm(log(IPAQ) ~ SC_IAT * PSQI, data = data_subset8)



plot(data_subset8$SC_IAT, residuals(model), xlab = "SC-IAT", ylab = "Residuals", main = "Residuals vs SC-IAT")  # Scatterplot of residuals vs SC-IAT

# Add a small constant to IPAQ to avoid log(0)
small_const <- 0.001  # Choose a small positive constant
```

```
data_subset8$IPAQ_adjusted <- data_subset8$IPAQ + small_const


# Apply log transformation to the adjusted response variable
model <- lm(log(IPAQ_adjusted) ~ SC_IAT * PSQI, data = data_subset8)


# 4. Multicollinearity (between predictors)
# Calculate correlation matrix for predictors
cor_matrix <- cor(data_subset8[, c("SC_IAT", "PSQI")])
print("Correlation Matrix:")
print(cor_matrix)



# 5. Independence (of errors)
# Durbin-Watson test
dwtest(model)  # Durbin-Watson test for independence


# Summary of the regression model
summary(model)


# Fit a linear regression model with interaction term
model <- lm(IPAQ ~ SC_IAT * PSQI, data = data_subset8)


# Print the summary of the model
summary(model)
```

```
#### ignore
# Load the required package
library(mgcv)

# Fit the GAM model with a moderator
model <- gam(IPAQ ~ s(SC_IAT) + s(PSQI) + s(SC_IAT, PSQI), data = data_subset8)

# Print summary of the GAM model
summary(model)
#### until here



## normal histogram
# Assuming data_subset9 contains the IPAQ variable
data_subset9 <- data_subset9[data_subset9$IPAQ < 30000, ]

# Replace "my_variable" with the actual name of your variable
IPAQ <- data_subset9$IPAQ

# Create a histogram
hist(IPAQ, main = "Histogram of my_variable", xlab = "Values")
```

```
# histogran AFFEXX
# Replace "my_variable" with the actual name of your variable
AFFEXX <- data_subset9$AFFEXX

# Create a histogram
hist(AFFEXX, main = "Histogram of my_variable", xlab = "Values")

# Add a normal distribution line
mu <- mean(AFFEXX)
sigma <- sd(AFFEXX)
curve(dnorm(x, mean = mu, sd = sigma), add = TRUE, col = "blue", lwd = 2)

## histogram of SC-IAT
SC_IAT <- data_subset8$SC_IAT

# Create a histogram
hist(SC_IAT, main = "Histogram of my_variable", xlab = "Values")

# Calculate the mean scores
# Calculate summary statistics for IPAQ, PSQI, and AFFEXX in data_subset9
summary_IPAQ <- summary(data_subset9$IPAQ)
summary_PSQI <- summary(data_subset9$PSQI)
summary_AFFEXX <- summary(data_subset9$AFFEXX)
summary_SC_IAT <- summary(data_subset8$SC_IAT)
```

```
# Print summary statistics
print(summary_IPAQ)
print(summary_PSQI)
print(summary_AFFEXX)
print(summary_SC_IAT)

# Calculate standard deviation for IPAQ
sd_IPAQ <- sd(data_subset9$IPAQ)

# Calculate standard deviation for PSQI
sd_PSQI <- sd(data_subset9$PSQI)

# Calculate standard deviation for AFFEXX
sd_AFFEXX <- sd(data_subset9$AFFEXX)

# Calculate standard deviation for SC_IAT in data_subset8
sd_SC_IAT <- sd(data_subset8$SC_IAT)

# Print the results
print(sd_IPAQ)
print(sd_PSQI)
print(sd_AFFEXX)
print(sd_SC_IAT)

## descriptive data of the sample participants, age, gender etc.
```

```
# Convert data to numerical format
data_clean <- as.data.frame(lapply(data_clean, as.numeric))

# Delete the first row
data_clean <- data_clean[-1, , drop = FALSE]

# Assuming 'data_clean' is your data frame containing the variable 'C101_01'
mean_C101_01 <- mean(data_clean$C101_01, na.rm = TRUE)

print(mean_C101_01)

summary_age <- summary(data_clean$C101_01)

# Print summary statistics
print(summary_age)

sd_age <- sd(data_clean$C101_01)

# Print the results
print(sd_age)

# Assuming 'data_clean' is your data frame containing the variable 'C104'
counts <- table(data_clean$C105)
print(counts)
```

```
counts2 <- table(data_clean$C106)
print(counts2)

# historggram PSQI
PSQI<- data_subset9$PSQI

# Create a histogram
hist(PSQI, main = "Histogram of my_variable", xlab = "Values")

# Fit the linear regression model
model <- lm(IPAQ ~ SC_IAT + PSQI, data = data_subset8)

# Plot scatterplots of predictors against the outcome variable
plot(data_subset8$SC_IAT, data_subset8$IPAQ, xlab = "SC_IAT", ylab = "IPAQ", main
= "Scatterplot of SC_IAT vs IPAQ")
abline(lm(IPAQ ~ SC_IAT, data = data_subset8), col = "red")  # Add regression line

plot(data_subset8$PSQI, data_subset8$IPAQ, xlab = "PSQI", ylab = "IPAQ", main =
"Scatterplot of PSQI vs IPAQ")
abline(lm(IPAQ ~ PSQI, data = data_subset8), col = "red")  # Add regression line

# Perform Spearman correlation test between IPAQ and SC_IAT
cor_test_IPAQ_SC_IAT <- cor.test(data_subset8$IPAQ, data_subset8$SC_IAT, method =
"spearman")
```

```
    # Print the result
    print(cor_test_IPAQ_SC_IAT)

    # Perform Spearman correlation test between IPAQ and PSQI
    cor_test_IPAQ_PSQI <- cor.test(data_subset8$IPAQ, data_subset8$PSQI, method =
    "spearman")

    # Print the result
    print(cor_test_IPAQ_PSQI)

# Print the mean value
print(mean_time_sum)

# Ensure the PSQI scores are within the valid range
data_subset8 <- data_subset8[data_subset9$PSQI >= 0 & data_subset8$PSQI <= 11, ]

# Create a frequency table of the PSQI scores
psqi_frequency <- table(data_subset8$PSQI)

# Print the frequency table
print(psqi_frequency)

#install package
if (!require(Hmisc)) {
  install.packages("Hmisc")
```

```
}
library(Hmisc)


# Select the relevant columns for the correlation analysis
variables <- data_subset8[, c("IPAQ_adjusted", "PSQI", "AFFEXX", "SC_IAT")]


# Compute the correlation matrix along with p-values
correlation_results <- rcorr(as.matrix(variables))


# Extract the correlation matrix and p-value matrix
correlation_matrix <- correlation_results$r
p_value_matrix <- correlation_results$P


# Print the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)


# Print the p-value matrix
print("P-Value Matrix:")
print(p_value_matrix)
```