The influence of age and sleep on visuo spatial working memory.

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Abstract

Our visuo-spatial working memory (VSWM), a cognitive component responsible for wayfinding and arithmetical challenges, is negatively related to aging according to prior studies. At the same time, aging is related to a decrease in sleep quality. However, the triangular relation of these three variables is unknown. This current research aims to identify the direct relation between VSWM and age and sleep. Additionally, we tested if the relation between VSWM and age can indirectly be explained by sleep duration and sleep variability. Finally, the explorative part of the study looked at the effect that sleep duration the night before testing has on VSWM performance. Unique about this study is the use of tappigraphy as a measure for sleep. Tappigraphy is a naturalistic way of deriving data from people's smartphone touches, allowing for the calculation of sleep duration and variability. The study included 151 participants, 99 for the explorative analysis, who installed an app on their smartphone (tappigraphy measure) and additionally had to complete a VSWM performance task (Corsiblock task). The analysis confirmed the negative relation between age and VSWM, but did not find a relation between sleep duration, variability and sleep the night before testing and VSWM. Additionally, no mediating effect of sleep on the relation between age and VSWM was found. In conclusion, while age and VSWM seemed related the sleep variables of current study did not show any relation to VSWM. This could be partially be explained by the limitations of this study. Future research should focus on constructs of sleep that do not deviate much from current literature. Plus, future research should aim to validate tappigraphy for an older population.

Keywords: visuo-spatial working memory, VSWM, age, sleep duration, sleep variability, tappigraphy

Author contribution: The current thesis is based on an existing dataset. Data reduction was performed by Arko Ghosh. Sven van Es developed the research question and performed the study described here individually and was responsible for the data analysis and report.

The influence of age and sleep on visuo-spatial working memory

A decline in working memory function is a prevalent occurrence amongst older adults (Craik & Rose, 2012). This decline can have a multitude of reasons since memory is a complex construct associated with many different structures in the brain. Apart from aging, research on sleep has shown that certain sleep components are negatively related to both working memory (Frenda & Frenn, 2016; Richards et al., 2017) and visuospatial attention (Bocca & Denise, 2006). A construct that is part of our working memory, responsible for wayfinding (Hund, 2016), is our visuo-spatial working memory (VSWM). However, while the relation between age and sleep on working memory has been given substantial attention, the relation between age and sleep on VSWM has not. Therefore, the focus of this research is to identify if there is a triangular relation between visuo-spatial working memory, age and sleep.

Visuo-spatial working memory

As a part of our working memory, VSWM is a cognitive component that temporarily stores visuo-spatial input (Logie, 1995). This concept originates from Baddeley and Hitch (1974) first conception of working memory, which divided working memory into three parts: 1. Visuo-spatial sketchpad, 2. Phonological loop, and later 3. The Central executive. The visuo-spatial sketchpad and phonological loop are devoted to store information to their own domain, being either visuo-spatial or phonological information (D’Amico & Guarnera, 2005). The central executive is assumed to coordinate these two systems. Coordination could take the form of inhibiting irrelevant information, temporarily activating long-term memory and switching between retrieval plans or strategies when needed (Baddeley, 1996; D’Amico & Guarnera, 2005). Baddeley’s visuo-spatial sketchpad, comprised of VSWM, contributes to many important day-to-day activities, such as wayfinding (Hund, 2016) and arithmetical tasks (D’Amico & Guarnera, 2005). During wayfinding the visuospatial sketchpad retains visual and spatial cues, such as maps, directions and patterns which is needed to preserve an integrated representation of the space around us (Baddeley, 2003). This caters a base for wayfinding and direction giving (Hund, 2016). Studies focussed on wayfinding and working memory often use a dual task paradigm, where a second spatial or vocal task needs to be completed during the primary wayfinding task. What is generally found, is that especially when spatial tasks are chosen to be the dual task, people’s wayfinding is hindered (Garden et al., 2002; Meilinger et al., 2008). Another well-established way of testing VSWM performance is via the Corsiblock test (Corsi, 1972). During the Corsiblock test, participants are requested to successfully replicate a sequence of highlighted cubes. If participants succeed, they advance to the next sequence which adds one more highlighted cube to the sequence. The higher the completed sequence, the higher a participant’s VSWM performance score.

Age

The normal aging of healthy people is characterized by a reduction in working memory capacity (Fabiani, 2012; Klencklen et al., 2017). This same trend can be seen when looking at the relation between VSWM capacity and aging. VSWM declines as people get older (Kumar & Priyadarshi, 2013); older adults are particularly disadvantaged when processing visuospatial information (Jenkins et al., 2000); and older adults show age-related deficits specifically in the spatial domain (Chen et al., 2003). However, it can be questioned if the aging effect on VSWM follows a continuous declining pattern. Kumar and Priyardarshi (2013) have shown that before the age of 60 a steep decline in VSWM performance in relation to aging can be seen that flattens out at the age of 60, indicating that VSWM does not deteriorate much in older adults. Other research on VSWM performance acknowledged age differences between young and old adults (Rowe et al., 2009). However, they did relate part of the age difference to older adults not performing their best because they seem to be more susceptible to interference and off peak time testing.

Sleep and VSWM

Apart from age, sleep also has an effect on VSWM. Sleep can be categorized on different levels, as do the general effects of sleep. Research recommends that adults have at least an average of 7 hours of sleep per night on a regular basis (Espiritu, 2008; Watson et al., 2015). A sleep duration of less than 7 hours per night could, apart from many physical discomforts, lead to an increase in errors and greater risk of accidents (Watson et al., 2015).

Next to sleep duration, sleep fragmentation, the clinical term for sleep disruption, has shown to have its effects on people's cognitive abilities. It can affect cognitive processes such as arousal and vigilance but also processes such as memory and executive function (McCoy & Strecker, 2011). Rat studies (Ward et al., 2009) also showed that sleep fragmentation impairs a rat's ability to retain spatial reference memories; however, in the same experiment it did not impair spatial working memory.

Partial Sleep Deprivation (PSD: less than 7 hours of sleep on multiple consecutive nights) can be the result of low sleep duration and/or sleep fragmentation. PSD is associated with a wide range of physiological and psychological effects, including a negative effect on working memory (Frenda & Frenn, 2016; Richards et al., 2017) as well as on visuospatial attention (Bocca & Denise, 2006).

Sleep measures

The way sleep and aspects of sleep are measured provide challenges. Best practices of sleep assessment include: polysomnography, videosomnography, actigraphy and subjective reports such as sleep questionnaires and diaries (Sadeh, 2015). Each one of these have their advantages and disadvantages. For instance, polysomnography provides very detailed information on sleep but is expensive, in a lab-environment and considered intrusive. Videosomnography is relatively non-intrusive but requires home installation and is limited by sleeping positions. Actigraphy is cost-effective and non-intrusive but provides limited data on sleep. Lastly, subjective reports are probably the most cost-effective and easiest to provide but the data that the subject provides can be biased (Sadeh, 2015). Apart from this, research has shown that different assessment methods can become moderating variables during sleep research. For instance, a meta-analysis from Ohayon et al. (2004) indicated that polysomnography studies found significantly larger correlations in comparison to actigraphy when looking at the relation between age and total sleep time.

Tappigraphy

A new and promising sleep measure involves looking at people's smartphone touchscreen events, called 'tappigraphy' (Borger et al., 2019). Tappigraphy is a naturalistic way of utilizing the widespread use of smartphones amongst people, in order to derive data from touchscreen events. The advantages of this proxy of measuring sleep include being less obtrusive than polysomno- or videosomnography and less prone to biases that occur with self-reports. During the research of Borger et al. (2019) the app TapCounter (QuantActions Ltd, Lausanne, Switzerland) was used to gather exact timestamps of all touchscreen interactions a participant made. These raw touchscreen timestamps could then be processed via MATLAB (MathWorks, 2021) using algorithms produced by QuantActions Ltd (Lausanne, Switzerland) to predict participants' sleep duration. An important note, the population sample consisted mainly of young adults. Therefore, generalizability of the results to other age groups should be addressed carefully. The results of their research showed that recording young adults smartphone touches is a legitimate proxy measure for sleep. Subsequently, the current research used tappigraphy and the 'sleep'-algorithms provided by QuantActions Ltd (Lausanne, Switzerland) to define people their sleep duration and variability.

Sleep and Aging

To create a complete picture of the relation between VSWM, sleep and age it is also important to look at how ageing influences sleep. There are many different aspects of sleep which are measurable. However, with the research of Borger et al. (2019) as a reference on what to measure to define sleep, we chose to focus on two aspects of sleep. These two aspects include sleep duration and sleep variability.

Sleep duration

A meta-analysis on quantitative sleep parameters across the human lifespan has shown that age differences occur when looking at total sleep time (TST) (Ohayon et al., 2004). The general consensus is that when people get older their total sleep time decreases. Important are the moderating variables that were found. Both recording methods and time of recording moderated the relation between age and TST, in a young population. When looking at adults it has been proven that excluding participants with mental or physical disorders, substance abusers and adults with sleeping disorders yields larger effect sizes between age and TST. Another noteworthy finding in the meta-analysis of Ohayon et al. (2004) was the relation between age and TST. This relation was found to be higher in studies that compared young adults with middle-aged adults and young adults with older adults. When researchers only included participants of 60 years or older, the association was non-significant. This signals that TST does not decline in a population of older adults.

Sleep variability

Besides sleep duration there is also sleep variability. The time we go to bed and wake up the next morning is rarely ever the same. This causes variability in our sleeping patterns that disturbs the synchronisation of a person’s sleep drive and circadian rhythm (Duncan et al., 2016). When these variabilities in sleep are highly mismatched with daily activities, as is the case with shift workers, a multitude of health problems can occur (Gooley, 2016; Leproult et al., 2014). However, the vast majority of people is not exposed to this kind of shift work. Yet, everyone shows some kind of sleep variability. Interestingly, we show these variabilities across different ages. Young adults and adolescents tend to spend more time in bed on free days as compared to workdays (Gooley, 2016). Subsequently, the transition to retirement shows that older adults go to bed later and sleep longer than when they were working (Hagen et al., 2016). This day-to-day variability of sleep duration has shown to negatively influence subjective sleep quality as well as our subjective well-being (Lemola et al., 2013).

Sleep duration the night before testing

Interestingly, when looking at the effect of sleep on either physical or cognitive states, research often focuses on sleep quality in extended periods. The effect that one night of sleep has on physical and/or cognitive states is often not looked into and possibly overlooked. What is known on the effect of one poor night sleep is that it negatively influences the way people feel, increased depression levels, increased anxiety, increased stress levels, increased heartrate and it decreases simple components of cognitive tasks (Barnett, 2008). Additionally, knowing that chronic sleep restrictions can lead to deterioration of spatial working memory performance, research from Hennecke et al. (2020) also showed that acute sleep restriction can have its negative effects on spatial performance tasks. During their research they showed that when participants had been chronically deprived of sleep, had one night of recovery sleep and then suffered acute sleep loss they were more vulnerable to the effects of acute sleep loss than participants that had not been suffering from chronic sleep loss. These effects of acute sleep loss translated into a decrease in spatial working memory performance. However, not only shorter than average sleep times can have negative influences, as sleeping too long can also have detrimental effects on a person's health (Youngstedt & Kripke, 2004). To our understanding, the effect of poor sleep quality the night before doing a test that measures VSWM has been barely researched, even though as described earlier, a decrease in VSWM can have consequences on human performance. Therefore we want to look at this in an explorative manner.

Aim

In sum, literature suggests the possibility of a triangular relation between VSWM, age, and sleep quality. However, prior research on this triangular relation has not been conclusive. The question to be answered is whether direct relations between VSWM and age also exist if differences in sleep quality are taken into account. As earlier stated, a new naturalistic approach of measuring sleep, called tappigraphy (Borger et al., 2019), will be used. Overall, expected is that this method illustrates sleep more naturalistically than regular laboratory settings currently do. Nevertheless, it needs to be taken into account that generalizability of this sleep measure has thus far only been proven for younger adults. Apart from the sleep measure people's VSWM performance will also be collected through online testing with the Corsiblock test.

First of all, we will look at the relation between age and VSWM. Earlier research on this relation shows that as people get older their VSWM declines (Kumar & Priyadarshi, 2013). However, it is unsure if this decline follows a continuous pattern after the age of 60 (Kumar & Priyadarshi, 2013). Alongside with establishing a relation between age and VSWM we also want to look at the relation between sleep and VSWM. We know that cognitive processes such as memory function and visuospatial attention are affected by sleep fragmentation and sleep deprivation (Bocca & Denise, 2006; McCoy & Strecker, 2011). By looking at the relation between sleep and VSWM we aim to better understand the process that is going on and the effects that each sleep variable (duration and variability) contributes.

After having looked at these dual relations we want to look at the relation between VSWM, age and the influence of sleep. This allows us to answer our research question: Can the decrease in VSWM performance as people age be partially explained by people's decrease in sleep quality (duration and variability) as they get older. Together with answering this research question, we plan on looking in an explorative way at the effect that one night sleep prior to testing has on VSWM performance. Apart from this being an unexplored area, it also contributes to understanding the relation between sleep and VSWM. The reason why is that the VSWM performance we measure during our research often depends on a single test made. If this VSWM test was made after a bad night sleep it could possibly misrepresent the relationship between sleep, age and VSWM. More specifically, there is a chance a serious proportion of our sample experienced a bad night sleep prior to testing for VSWM which caused them to score relatively low. Meanwhile, their average sleep quality is deemed high by our sleep measure for averages, therefore we expect high(er) VSWM scores. If there is a relation between sleep the night before testing and VSWM this could influence the results and interpretation of our research question. All in all, with this research we hope to contribute to the field of aging, sleep and VSWM and more specifically to the interaction between them.

Hypotheses

Research on the relation between age and VSWM seems conclusive. When people get older their VSWM declines (Kumar & Priyadarshi, 2013). Therefore, we hypothesize that older adults have lower VSWM performance than younger adults. The following important relation we want to look at is the relation between sleep and VSWM. It is clear that components of sleep can effect memory and executive function (McCoy & Strecker, 2011). In addition, sleep deprivation has also been proven to negatively affect working memory and even visuospatial attention (Frenda & Frenn, 2016; Richards et al., 2017; Bocca & Denise, 2006). Therefore we hypothesize that lower sleep quality (deviating sleep duration, and high variability) correlates with lower VSWM performance. Thirdly, in order to see if the decline in VSWM with aging is mediated by sleep quality, we will look at the interaction effect between these factors. With older adults having poorer sleep quality and a decline in VSWM because of their age, we hypothesize that the effect of age on VSWM performance can be (partially) explained by the mediating factor sleep quality.

Finally, we will also be looking, in an explorative way, at the influence that ‘sleep quality of the night prior to testing’ has on the results of testing VSWM performance. As earlier stated, one night of poor sleep can lead to both physical, cognitive decline (Watson et al., 2015; McCoy & Strecker, 2011) and under circumstances even to a decrease in spatial working memory performance (Hennecke et al., 2020). Therefore, our expectation is that VSWM performance scores are lower when subjects had a poor night sleep.

Method

Design

This study is part of a larger longitudinal study carried out by CodeLab and Leiden University through the website www.agestudy.nl. The overarching aim of that study is to identify changes in behaviour that are associated with ageing over the span of three years with the help of smartphone behaviour.

This study focused on understanding the effect of sleep on VSWM in an aging population. The study used a within-subjects design, with a correlational approach. The independent variable for the study is: Age. The dependent variables are Corsi Block performance score and the smartphone touchscreen taps (as a proxy for sleep duration and sleep variability). The smartphone tap data will be collected with the TapCounter App, designed by QuantActions LTD (Lausanne, Switzerland). The cognitive testing, in this case Corsi Block test performance will be done on the online platform of www.agestudy.nl.

Participants

The study included 180 participants. Criteria for participations was that participants had to be adults, preferably equally distributed over the age span of 18+ to 99+ years old. Participants had to be Android-smartphone users, be cognitively healthy, have no finger-related traumas and speak either Dutch or English. In order to do the online testing, participants also needed to have access to either a laptop or desktop computer. A set of exclusion criteria was set up, see ‘Analysis’, which left the sample with 151 participants for our hypothesis testing. For the explorative analysis 99 out of the 180 participants data was used. Specific exclusion criteria can be found under ‘Analysis’. Participants could choose to be compensated. This compensation entails €7/hour of online testing on www.agestudy.nl with a maximum of €80. Students of Leiden University also had the option to obtain course credits to a maximum of 2 hours testing time. Students need to participate in the study for at least two months in order to earn the credits.

Procedure

Participants were asked to sign-up on www.agestudy.nl. During signing-up, participants need to make sure they have downloaded the TapCounter app. The data collected through the TapCounter app was linked to the test scores made on www.agestudy.nl. Participants can, to their own liking, complete cognitive tests on www.agestudy.nl every month or more when they like to.

Apparatus

The software that was used during research included the TapCounter app, designed by QuantAction LTD (Lausanne, Switzerland). This is a behavioural assessment tool that collects smartphone data. The app currently only runs on Android smartphones and needs to be installed via the GooglePlay store. After downloading, participants needed to follow a set of instructions in order to register. After registration, the app continuously runs in the background in order to collect data. Participants should not expect hindrance from this. The collected data is analyzed and used as proxy measures for sleep quality.

In order to analyse the rich amount of data that was gathered with the TapCounter app, we used MATLAB (version R2021a). While working with MATLAB we used algorithms provided by QuantAction LTD to quantify our sleep variables. After MATLAB the data was exported to Microsoft Power BI and Excel for filtering and cleaning up the data. In the end, the data was exported to SPSS (IBM SPSS Statistics, version 28), which was used in order to conduct the statistical analysis.

Task

The task used in this research to measure VSWM performance was the Corsiblock task (Corsi, 1972). The scores a participant can attain ranges from 0 (lowest) to 9 (highest). The way they can attain these scores is by reproducing a random highlighted sequence of blocks that increases in length after successful completion of a trial. More specifically, a participant is shown nine different cubes on screen. Each trial an ‘x’ amount of cubes is highlighted. After the cubes have been highlighted the participant is asked to reproduce the highlighted string of cubes in the correct order. A successful reproduction enables the next trial which increases the highlighted cubes by one more cube. Participants start with a trial of two highlighted cubes and if successful continue to a maximum of nine highlighted cubes. After two false reproductions the test is terminated. The highest completed reproduction is the VSWM score a participants receives. A study from Kessels et al. (2000) showed that healthy adults score an average of 6.2 blocks with 1.3 standard deviation. Before starting the Corsiblock task participants were required to do a warm-up task. After completing the Corsiblock task we asked participants if they were well-rested and did not experience any discomforts during the test. All in all, the warm-up task plus Corsiblock took participants anywhere between 10 to 20 minutes to complete, depending on how well they performed.

Analysis

The first step of the analysis was to check the data of the participants for missing or abnormal values. Participants were excluded from the analysis if one of the following conditions was met:

- Participants had no recorded sleep data
- Participants did not have one complete week (weekdays and weekend days) of sleep measurements, therefore not allowing to measure sleep variability.
- Participants did not complete or scored a zero on the Corsiblock test

After this selection, we also decided to exclude participants who recorded sleep duration averages or sleep variability averages of more than three standard deviations from the mean (sleep duration < 4:40 or > 13:10 hours; sleep variability > 2:02 hours). This last exclusion criterion was deemed necessary. It filtered out a small number of participants (4) that just slipped by the other exclusion criteria. However, including these participants with their highly deviating data would influence results and therefore influence the reliability and interpretation of the analyses. In total, this resulted in 29 exclusions for the analysis, leaving 151 participants. From these participants we gathered their accompanying data as measured with the Tapcounter App. This data was pre-processed by one of our supervisors Arko Ghosh via MATLAB. This process included putting the raw touchscreen timestamps in MATLAB. Subsequently, with the help of certain specific algorithms in MATLAB the touchscreen timestamps were processed into gaps in smartphone use during the circadian rest phase of participants. These gaps were labelled as 'sleep' for a participant. For more details on this process see the article of Borger et al. (2019). The data available was exported to Microsoft Excel and Microsoft Power BI and further processed for statistical analyses with SPSS. With the help of this data we calculated average sleep durations and average sleep variability. The average sleep duration was the calculated average of all recorded sleep durations. Prior to calculating averages, we excluded individual sleep measurements that deviated more than three standard deviations from the average of that participant. This was done to filter out failed attempts of measuring sleep. Sleep variability was defined as the difference in sleep duration between weekdays and weekend days. Weekdays included Sunday night's sleep up until Thursday night's sleep and weekend days included Friday night's and Saturday night's sleep. Generally speaking, this division is a depiction of a normal working week.

In order to calculate sleep variability for each participant we took the average sleep duration of weekdays and subtracted it by the average sleep duration of weekend days. The larger the difference from zero, whether it be a positive or negative number, the larger the sleep variability.

Initial research showed that sleep data measured with the Tapcounter app was a valid tool for younger adults (Borger et al., 2019). In order to check the reliability of the sleep data for older age groups we looked at anomalies of sleep duration and variability between the means and standard deviations in our sample. For this part of the study we divided our sample into three groups sorted by age. Groups included young adults (lowest to 30 years), middle age adults (31 to 60 years) and older adults (61 to highest). In addition, a one-way ANOVA was conducted to compare and look for differences in sleep duration and variability averages between the afore mentioned groups. For all our statistical testing we used an alpha-level of .05.

Our research included three hypotheses and an explorative part. The following part contains the relevant statistical methods for each hypothesis and the assumptions that needed to be tested for each statistical method.

For our first hypothesis we have two quantitative variables and only one independent variable, therefore we used a simple linear regression. Before doing the analysis we checked if the assumptions of linear regression were met:

- Independence: This was checked during data preparation.
- Normality: This was checked with a normal Q-Q plot. However with a relative large sample size (n = 151) the normality assumption should not be a deciding factor, as the central limit theorem states that having a large sample concludes that the assumption of normality is met (Ghasemi & Zahediasl, 2012).
- Linearity: This was checked with the help of a scatterplot.
- Homoscedasticity: This was also checked with a scatterplot.

If any of these assumptions were violated a nonparametric analysis in the form of Kendall's tau-b was conducted. The assumptions for this non-linear regression analysis are:

- Independence
- Scale of measurement: Both variables should be at least ordinal

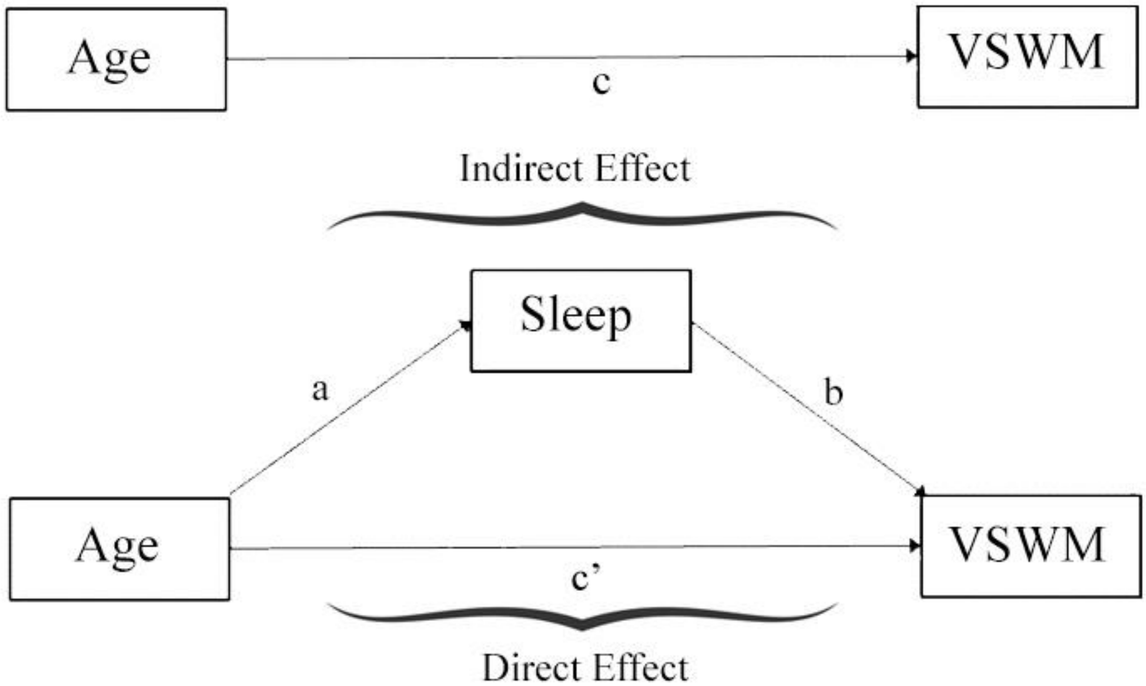
After looking at the relation between VSWM and age, we looked at the relation between sleep quality and VSWM. To test this hypothesis we used a multiple regression analysis in SPSS. The same assumptions as the simple linear regression apply, with the addition of:

- Multicollinearity: This was done by checking the variance inflation factor (VIF) values in SPSS. If each VIF value is below 10 the assumption is met.

The third hypothesis tested for an interaction between age and sleep on VSWM. This was done with the help of a mediation analysis. The mediation model can be seen in Figure 1.

Figure 1

Diagram of the mediation model used



Note. Line 'a' and 'b' together represent the indirect effect. Line 'c'' represents the direct effect. Line 'c' is the simple relationship between Age and VSWM without a mediating variable.

For the mediation analysis we used a comprehensive SPSS tool, called PROCESS 4.0 (Hayes, 2017). With the help of PROCESS we analyzed our data in two different ways: The first type of mediation analysis used Baron & Kenny's (1986) 4 step model. This method tests the four condition of mediation (Field, 2013):

1. The predictor variable must significantly predict the outcome variable in model 1;

2. The predictor variable must significantly predict the mediator in model 2;

3. The mediator must significantly predict the outcome variable in model 3;

4. The predictor variable must predict the outcome variable less strongly in model 3 than in model 1.

Important to note, is that because this method uses p-values it encourages an all-or-nothing approach (Field, 2013). Since we did not want to fully depend on this all-or-nothing approach we looked at another method of mediation analysis.

This approach used bootstraps methods in order to compute confidence intervals for the indirect effect of the mediation. This allowed us to simply report the degree of mediation that we observe, instead of looking for significant relationships. If the bootstrap interval did not include zero the mediation effect was deemed significant. In the case of a significant effect, we looked at Preacher and Kelley's (2011) effect size kappa-squared (k^2). This effect size expressed the indirect effect as a ratio to the maximum possible indirect effect that could have been found (Field, 2013).

For the explorative part of this study we looked at the effect that sleep the night prior to testing has on doing the Corsiblock test the following day. Out of the 151 participants that had been selected, 99 had all data that allowed for this analysis. Reasons for exclusion included:

- Participants completing the Corsiblock test before the initial sleep measurement
- Participants completing the Corsiblock test more than one day after the final sleep measurement
- Participants completing the Corsiblock test during sleep time, as measure by the Tapcounter app

In order to see if sleep night-before-testing data is a good predictor for VSWM we used a simple regression analysis with $sleep_{nbt}$ data as independent variable and Corsiblock spanscore as dependent variable. This analysis used the same process and assumptions as stated in the simple regression analysis of hypothesis 1. In addition to this simple regression, we conducted a second simple regression with sleep duration as independent variable with the same dependent variable. Results from prior hypothesis were not usable since the number of participants for this analysis was drastically lower. After both analysis we compared the results. This way we could see if $sleep_{nbt}$ is a good, better or worse predictor than sleep duration in relation to VSWM.

Results

For our hypotheses testing we had a total of 151 participants. Before the actual analysis we first looked at the differences in sleep duration and sleep variability averages between our three age groups. The results can be seen in Table 1 below:

Table 1

Sleep duration and variability averages for three age groups

Age groups	*N*	Sleep duration average *M (SD)*	Sleep variability average *M (SD)*
< 30 years	27	8:14 (1:12)	0:21 (0:19)
31-61 years	54	8:54 (1:12)	0:33 (0:23)
> 61 years	70	9:10 (1:23)	0:26 (0:20)
Total	151	8:54 (1:23)	0:28 (0:21)

Note. Units for sleep duration/variability are in hours: minutes

In addition, a one-way ANOVA (see Appendix A) was conducted to compare sleep duration and variability averages between ‘1 = lowest to 30 years’, ‘2 = 31 to 61 years’ and ‘3 = 61 to highest conditions’.

Sleep duration average: There was a statistically significant difference in sleep duration between groups ($F(2,148) = 4.561$, $p = .012$). A Tukey post hoc test revealed that the sleep duration average was significantly lower for group 1 (8:14 ± 1:12 hours, $p = .008$) compared to group 3 (9:10 ± 1:23 hours). There was no statistically significant difference between group 1 and group 2 (p = .102) and between group 2 and 3 (p = .517). This means that participants, in our sample, aged 61 or older sleep longer on average than people that are younger than 30.

Sleep variability: There was a statistically significant difference between groups for sleep variability ($F(2,148) = 3.098$, $p = .048$). Tukey's post hoc test however shows no significant differences between groups. Noteworthy for sleep variability is the difference between groups 1 and 2. Participants in age group 1 have less sleep variability (0:21 ± 0:19 hours) than group 2 (0:33 ± 0:23 hours). However, maintaining a significance level of $p < .05$ this relation is deemed non-significant at $p = .053$.

Hypotheses

Age and Corsiblock spanscore

A Pearson correlation coefficient was computed to assess the linear relationship between *Corsiblock spanscore* ($M = 5.40$, $SD = 1.18$) and *age* ($M = 53.98$, $SD = 16.99$). A negative correlation between the two variables was found, $r(151) = -.354$, $p < .001$. This $r = -0.354$ is considered a weak to moderate effect (Akoglu, 2018). Participants predicted Corsiblock spanscore is equal to 6.729 – (0.025 * age) score when age is measured in years.

Prior to conducting the analysis for the first hypothesis the assumptions of normality, linearity and homoscedasticity were assessed, and found to be supported (see Appendix A). Noteworthy was the division of age in our sample as this did not seem to be normally distributed in our sample (see appendix A). However, with the central limit theorem in mind it was no reason to assume the assumption of normality was violated, however, it was taken into consideration with the interpretation of the results.

Sleep duration and variability and Corsiblock spanscore

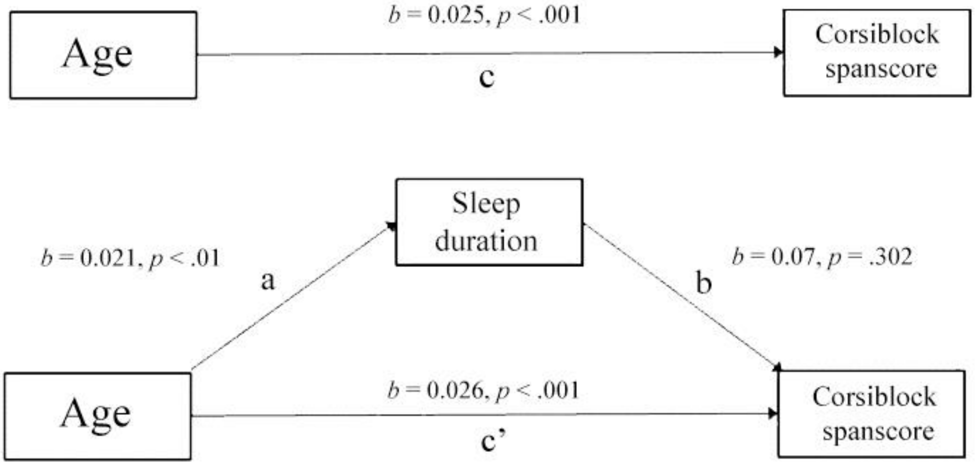
Before conducting the MRA, the assumptions of MRA were tested (see Appendix B). First, normal Q-Q plots and histograms indicated that sleep duration was normally distributed. Sleep variability showed deviations of normal distribution but as explained earlier with the central limit theory, this was no reason to assume the assumption of normality was violated. Second, inspection of the scatterplot of standardized residuals against standardized predicted values indicated that the assumptions of linearity and homoscedasticity were met. Third, VIF values of <10 (1.021 for both) indicated that multicollinearity would not interfere with the ability to interpret the outcome of the MRA. For more details and visuals of these assumptions, see appendix C. The MRA showed that sleep duration and sleep variability accounted for a non-significant 0.004% of the variability in Corsiblock spanscore (M = 5.40, SD = 1.18), R^2 = 0.000458, adjusted R^2 = -0.013, F (2, 148) = .034, p = .967. It was found that sleep duration non-significantly predicted Corsiblock spanscore (β = -0.01, p = .87), as did sleep variability (β = -0.01, p = .86).

Age, sleep and Corsiblock spanscore

In order to check the third hypothesis we conducted two varieties of mediation analysis. The mediation analyses looked at the effect of age on Corsiblock spanscore with sleep duration and sleep variability as mediating factors. The first mediation analysis was conducted with PROCESS v4.0 according to Baron & Kenny's (1986) 4 step model. Figure 2 shows that the mediator in our model does not significantly predict the outcome variable as 'b' is a non-significant effect with a p-value of .302. In addition, controlling for the mediator (sleep duration), the relation between Age and Corsiblock spanscore (c') did not decrease in significance level or became insignificant compared to the direct effect of Age on Corsiblock spanscore (c). Therefore, according to Baron & Kenny's (1986) 4 step model of mediation, we conclude that there is no mediation effect of sleep duration in our model.

Figure 2

Mediation model with sleep duration

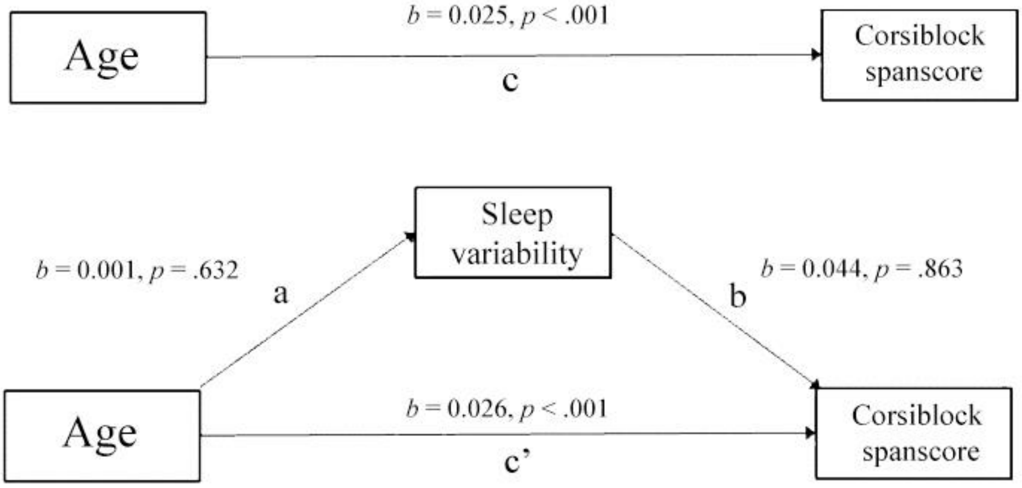


Note. The units for this analysis are numeric instead of time units. This was because PROCESS does not allow mediation analysis with variables that are in hours: minutes

Figure 3, which has sleep variability as a mediator, also shows no mediation effect. With a p-value of .863, the mediator sleep variability in this model does not significantly predict our outcome variable Corsiblock spanscore (b). Additionally, age and sleep variability also show a non-significant effect (a), $p = .632$. Finally, controlling for the mediator (sleep variability) the relation between age and Corsiblock spanscore (c') did not decrease in significance level or became insignificant compared to the direct effect of age on Corsiblock spanscore (c). Consequently, we conclude that for this analysis method, there is no mediation effect of sleep variability in our model.

Figure 3

Mediation model with sleep variability



Note. The units for this analysis are numeric instead of time units. This was because PROCESS does not allow mediation analysis with variables that are in hours: minutes

In addition to the classical approach for mediation, we also decided to use a bootstraps method in order to compute confidence intervals for the indirect effect of the mediation. For both mediating variables the confidence interval for the indirect effect is based on 5000 bootstrap samples. Regarding sleep duration we saw a non-significant (at α = .05) indirect effect of age on Corsiblock spanscore through sleep duration, b = .002, BCa CI [-.001, 005]. For sleep variability we identified an equal non-significant indirect effect of age on Corsiblock spanscore through sleep variability, b = .000, BCa CI [-.001, .001].

Explorative

Sleep night before testing and Corsiblock spanscore

For the explorative part we looked at the relation between sleep the night before testing and Corsiblock spanscore in comparison to the relation between sleep duration average and Corsiblock spanscore. Prior to conducting the analysis, the assumptions of simple linear regression were investigated (see Appendix C). After checking the assumptions, a Pearson correlation coefficient was computed to assess the linear relationship between *sleep duration the night before testing* (*M* = 8:53, *SD* = 1:41) and *Corsiblock spanscore* (*M* = 5.40, *SD* = 1.179). A non-significant positive effect between the two variables was found, $r(99) = .119$, $p = .242$. The same Pearson correlation was conducted to look at the correlation between *sleep duration average* (*M* = 9:01, *SD* = 1:19) and *Corsiblock spanscore*. This showed a non-significant negative effect, $r(99) = -.017$, $p = .865$.

Discussion

During this naturalistic study our aim was to learn more about the relation between age, sleep quality and VSWM. We looked at these constructs in direct relation to each other but also in a triangular relation, to see if mediation occurred. First off, we hypothesized that when people get older their VSWM declines. The conducted analysis showed that when people get older their performance on the Corsiblock task decreases, in other words their VSWM declines. Secondly, we hypothesized that having lower sleep quality relates to lower VSWM performance. Our analysis showed that neither sleep duration or sleep variability was related to Corsiblock task performance. Thirdly, we looked at mediation effects of sleep quality on the relation between age and VSWM and hypothesized that the effect of age on VSWM can be (partially) explained by sleep quality. With our analysis we saw that there was no sign of a mediation effect, sleep does not explain the relation between age and VSWM. Finally, the explorative part looked at the influence that sleep duration the night before testing had on the results of VSWM performance. After the analysis it was clear, that for our sample, sleep duration the night before testing is not related to Corsiblock test performance.

In short, the majority of our expectations were not met. This next section explains our findings more in-depth by looking at contrasts between this current study and existing literature. In addition, implications of the results, recommendations for future research and methodological and conceptual limitations are discussed. Lastly, a conclusion about the current study is drawn.

Before addressing the main findings in depth, it is necessary to first look at the results of our validation for tappigraphy as a sleep measure for different age groups. Borger et al. (2019) have established that for a younger population, tappigraphy is a valid method of sleep. Our population sample was skewed, leaning more to a population of older adults (>61 years). With the older adults we noticed a difference in sleep duration between them and our youngest population (<30 years). Namely, they recorded a higher average sleep duration of more than one hour in comparison to the younger population. This finding is in contrast with the general consensus in current literature. This states that when people get older their total sleep time decreases (Ohayon et al., 2004). A possible explanation for this contradiction can be due to usage differences of smartphones between different age groups. It is safe to say that large parts of current younger generations grow up with a smartphone and use it extensively. For older adults a smartphone is most likely a useful gadget rather than a basic necessity, since they have spent the majority of their lives without one. They may not use them as much late in the evening and may also not use them much early in the morning, which is the critical period for determining sleep duration. This difference in smartphone usage could be a feasible explanation to why older adults record longer sleep duration averages compared to younger more smartphone dependent people when using tappigraphy. In order to further establish tappigraphy as a sleep measure, future studies should focus on validating tappigraphy as a sleep measure for all ages. This could mean trying to change older adults their smartphone. However, a more attainable way would probably be to gather more sleep data from older adults with the help of tappigraphy and compare this to actigraphy measurements, a well-established sleep measurement tool. After comparison the sleep measurement algorithms in MATLAB should be adjusted to reflect sleep results that are in line with actigraphy. This way, this new naturalistic and non-intrusive method will prove to be even more of a reliable sleep measure.

A relation that was found, and in line with prior research, was that age and VSWM showed a negative relation. Meaning, when people get older their VSWM declines. This was considered to be a weak to moderate effect. Validating this relation of declining VSWM as people get older, as predicted by prior literature (Chen et al., 2003; Jenkins et al., 2000; Kumar & Priyadarshi, 2013), laid a foundation for the mediation analysis.

Prior to the mediation analysis we looked at the relation between VSWM and our two variables for sleep quality, sleep duration and sleep variability. Our analysis showed no reason to believe that sleep duration and variability had a relation with VSWM. This finding was in contrast with our theoretical basis and our expectations. Existing literature stated that sleep disruption can influence processes such as memory function (McCoy & Strecker, 2011), and sleep deprivation was related to negative effects on working memory (Frenda & Frenn, 2016; Richards et al., 2017) and even visuospatial attention (Bocca & Denise, 2006). However, comparability of the theoretical framework and results of this study can be debated. This is because the cognitive constructs and sleep measures from our theoretical framework differ slightly from what was measured in our study. Memory function and visuospatial attention have overlap with VSWM and sleep fragmentation and sleep deprivation can be measured with sleep duration, leading to our expectations. But to translate these constructs to VSWM and sleep duration/variability and the relation between them was most likely a step to far. Future research should not deviate too much from the relationships that have been established and investigate more around these constructs. For example, instead of looking at the relationship between VSWM and sleep duration a first step would be to look at the relation between VSWM and sleep fragmentation or sleep deprivation. This would contribute to the field of VSWM and sleep while keeping research close to what has already been researched. Still, finding no relation between VSWM and sleep duration/variability should not be disregarded. It is plausible that VSWM and the amount of sleep and difference in sleep between week and weekend days do not share a relation and this was a first step in proving so.

For the mediation analysis we looked at the relation between age and VSWM with sleep duration and variability as mediators. Both of our mediation testing methods showed no mediation effect of the sleep variables on the relationship between age and VSWM. This came as no surprise as our previous testing showed no relation between the two sleep variables and VSWM, which was one of the conditions for mediation. In short, for our sample there was no indirect effect of sleep duration and variability that explained the relation between age and VSWM. Interesting to mention, during the mediation analysis we did see a confirmation of the relation between age and sleep. As people get older their sleep duration increases. A small note, this effect could be due to tappigraphy not being optimal yet for older adults, as explained earlier. For sleep variability this relation did not occur.

After having looked at the effect of sleep over longer periods of time, we also wanted to investigate acute effects of sleep duration on VSWM. We questioned if the amount of sleep a person has the day before their VSWM is measured is related to their VSWM performance that day. Research from Hennecke et al. (2020) had stated earlier that acute sleeping restrictions can have its negative effects on spatial performance. Additionally, Barnett (2008) showed that one poor night of sleep can negatively influence both physical and cognitive constructs. However, our research showed that for our population the amount of sleep the night before testing is not related to people their performance on a VSWM task the next day. In comparison to the literature, this was an unexpected yet explainable difference. Current literature seems to focus on acute sleep deprivation in relation to physical or cognitive constructs, whereas our study looked at the overall relation between the amount of sleep before testing and a cognitive construct. It is likely that our sample contained people that were somewhat sleep deprived in relation to their average night sleep. However, we did not control for this by looking at the difference between their one night sleep measures in comparison to their sleep average. For future research it would be useful to include this in order to see if people that sleep substantially less before testing, as compared to their average sleeping time, show a difference in VSWM performance.

When interpreting the results of the current study there are several limitations that have to be taken into account. With regards to methodical limitations the skewed population regarding age needs to be taken into consideration when interpreting results. In our sample almost half of the population was older than 61 years. This could mean that our results are more driven by the older age group in contrast to an evenly distributed age sample. Still, with a sample size of 151 participants in which the younger generation, the smallest group, accounted for approximately 20% (see table 1) it is justifiable to state that all ages were represented during testing. Another methodical limitation regarding age applies to tappigraphy as a sleep measure for older adults. As implied earlier, the older adults in our sample had substantially longer sleeping averages in comparison to the younger adults. This was in contradiction with current sleep literature, which stated that as people get older their sleep time decreases (Ohayon et al., 2004). We theorised that this could be due to tappigraphy not being optimised for older adults yet (see, p. 23). Interpretation-wise it is important to understand that this tappigraphy implication for older adults, in combination with a sample size in which older adults represent a large proportion, could have influenced results.

With regards to more conceptual limitations of this research, we argued that the constructs we looked at occasionally deviated too much from related constructs that were used as the theoretical basis (see, p.24). After having conducted our research, we think it would have been beneficial to this study if its important constructs were chosen closer to our theoretical framework. An example would be to investigate sleep deprivation instead of sleep duration in regard to VSWM, as our theoretical framework implied more on the effects of sleep deprivation. This way the current study could possibly contribute more to existing literature as comparisons and contrasts would have been closer related to each other.

To conclude this study, we confirmed the negative relation between age and VSWM. When people get older their VSWM tends to decline. Knowing that VSWM can influence wayfinding (Hund, 2016) and arithmetical task (D'Amico & Guarnera, 2005), future research on this should take this negative relation into consideration. Furthermore, in our sample, there was no relation between sleep duration and variability and VSWM. This finding was in contrast with our expectations but could partially be explained by the limitations of this research. Lastly, our analysis showed that the relation between age and VSWM could not be explained by an indirect effect of either sleep duration or variability. For the explorative part of the study, we found that the duration of sleep the night before testing for VSWM had no influence on VSWM test performance. For future research, we advise that when looking at the influence of sleep on VSWM to first look at constructs of sleep that are closer related to VSWM, for instance sleep deprivation. Additionally, future research should consider to further validate tappigraphy as a measure of sleep. Especially for older adults, since we found that for our sample older adults had longer periods of not touching the phone in the night time – a measure that we used as a proxy for sleep duration. This led to believe that older adults sleep less in comparison to younger adults, which is in contrast with current literature on sleep.

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Appendix A

This appendix includes the assumptions of a linear regression for hypothesis 1. The amount of participants was 151. The first assumption was to check for normality. The normal Q-Q plot for age, Figure A1, shows that data deviates from the diagonal line of normal distribution. Figure A2 shows that our sample has heavy presence of older adults (>60 years). The age group 30 to 50 years seems underrepresented. As explained earlier this was not a reason to assume the assumption of normality is violated, however, it was taken into consideration with the interpretation of the results.

Figure A1

Normal Q-Q plot for age

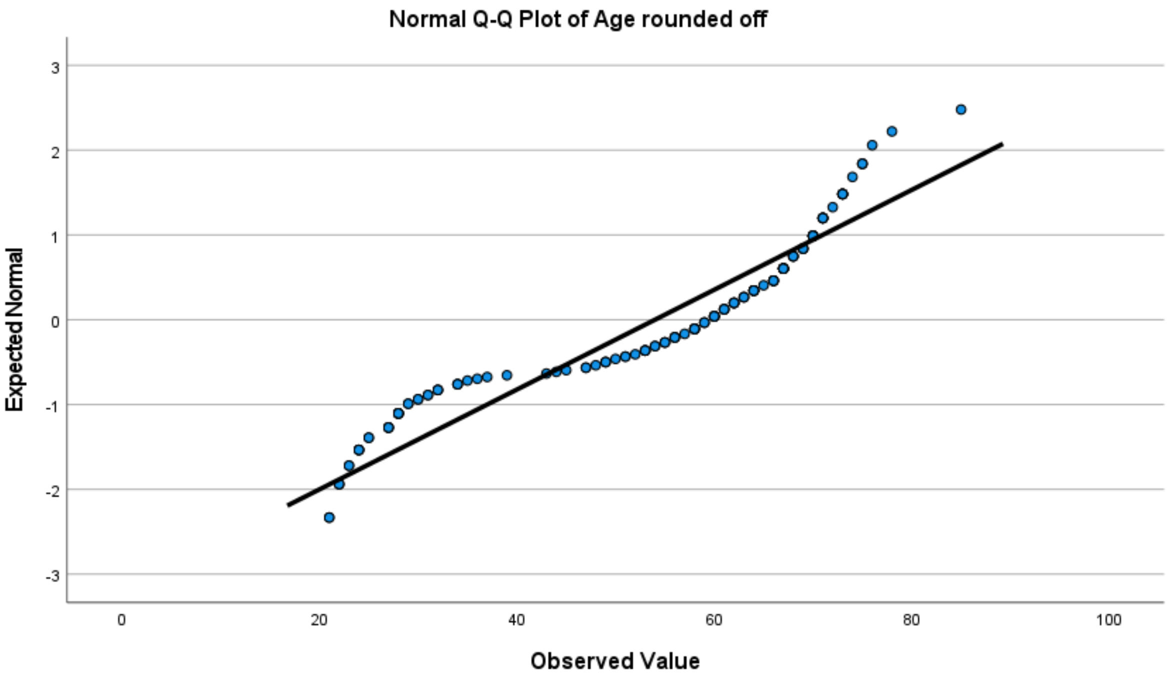


Figure A2

A histogram of our age sample

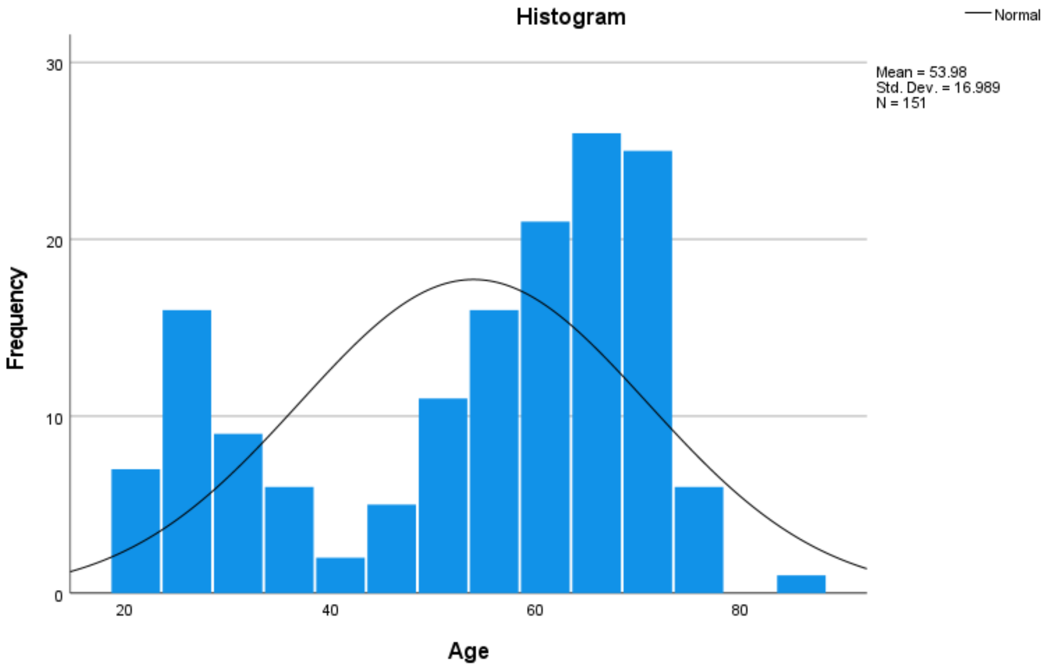
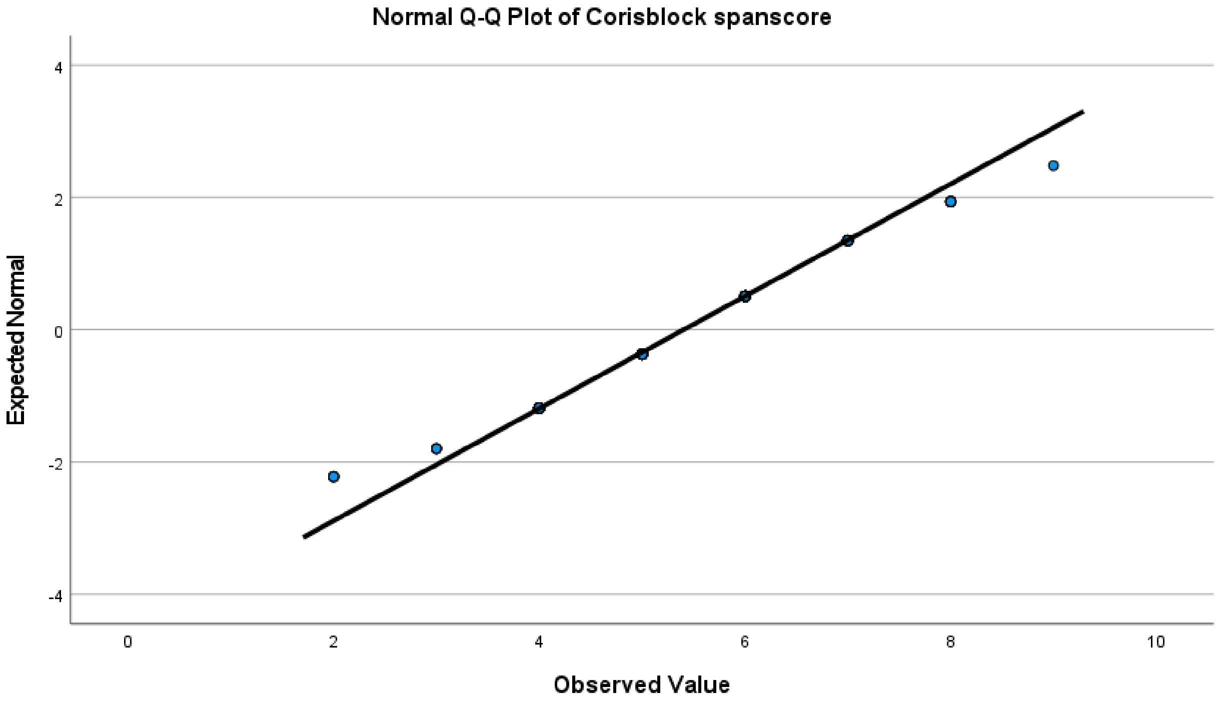


Figure A3 shows that Corsiblock spanscore appears to be normally distributed, as the values are close the diagonal line that indicates normal distribution.

Figure A3

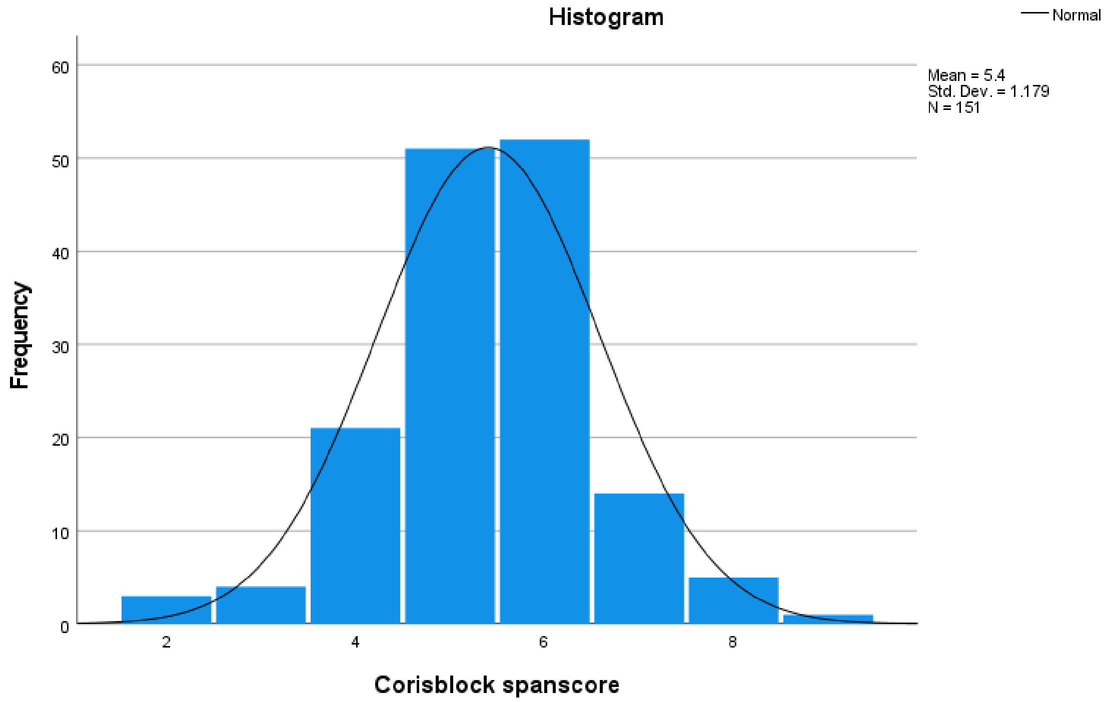
Normal Q-Q plot of Corsiblock spanscore



The normal distribution of data for Corsiblock spanscore was also clearly visible in Figure A4.

Figure A4

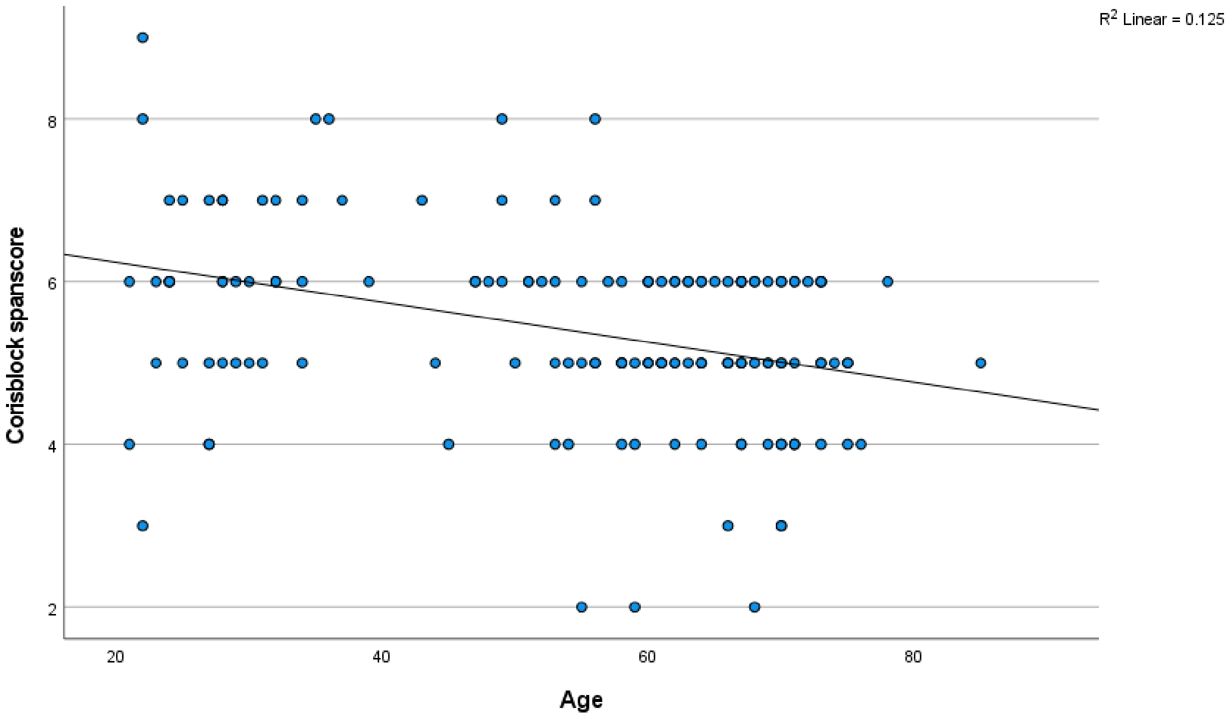
A histogram for Corsiblock spanscore



The scatterplot, in figure A5, was created to check for linearity and homoscedasticity. It indicates a rough linear relationship. Furthermore, the relationship between the two variables appears to be homoscedastic as there is roughly the same amount of variability in Corsiblock spanscore at all levels of age.

Figure A5

Scatterplot for Corsiblock spanscore and age



Appendix B

Worked out below are the assumption for the MRA that was used for hypothesis 2. The variables looked at are sleep duration, sleep variability and Corsiblock spanscore. However, the assumption for Corsiblock spanscore can be found in appendix A.

The normality Q-Q plot of sleep duration, figure B1, shows a clear division of data along the diagonal line. This indicates a normal division of data. Figure B2, the histogram on sleep duration also shows indicates that data is normally distributed.

Figure B1

Normal Q-Q plot of Sleep duration

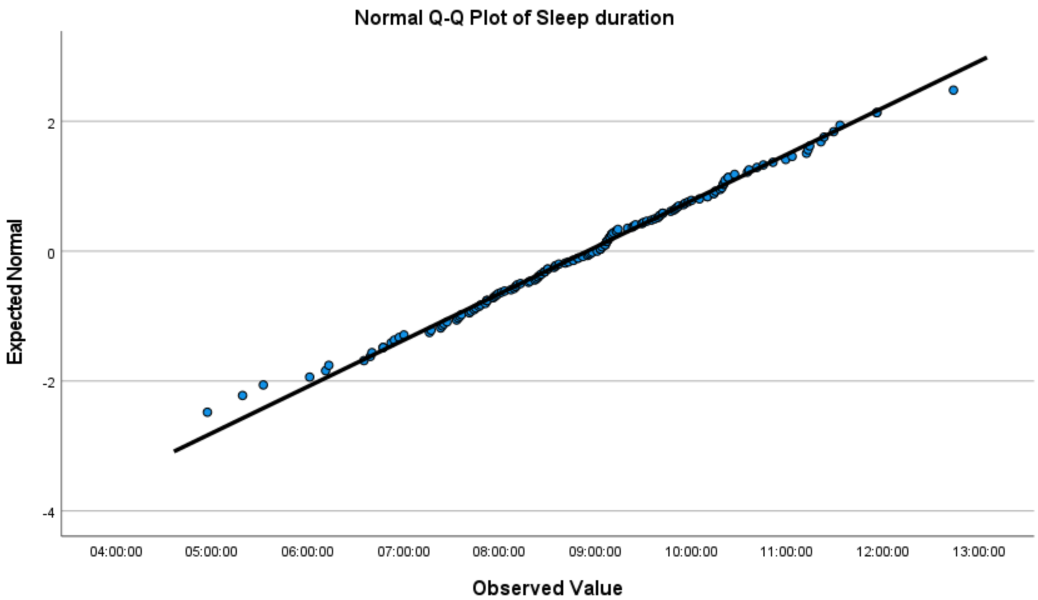
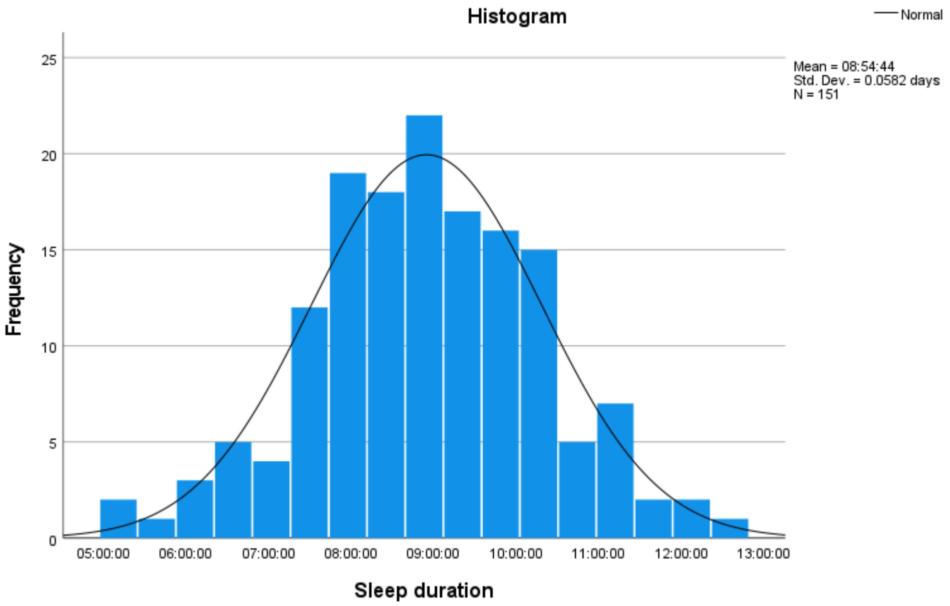


Figure B2

Histogram of Sleep duration



When checking the normality principle of sleep variability, see Figure B3 and B4, we found that the data does deviate from a normal distribution on some points. As explained earlier with the central limit theory, this was no reason to assume the assumption of normality is violated. Also noteworthy was a suspected outlier, which can be seen on the top right side of the Plot. Even though this outlier can be considered an outlier in this sample of N=151 as it is more than 3SD's from the mean, it was not an outlier during our selection process when N was 160 (sleep variability of this sample is 1:55 hours which is lower than the threshold of 2:02 hours). Therefore, we did not exclude this participant in our measurement.

Figure B3

Normal Q-Q plot of Sleep variability

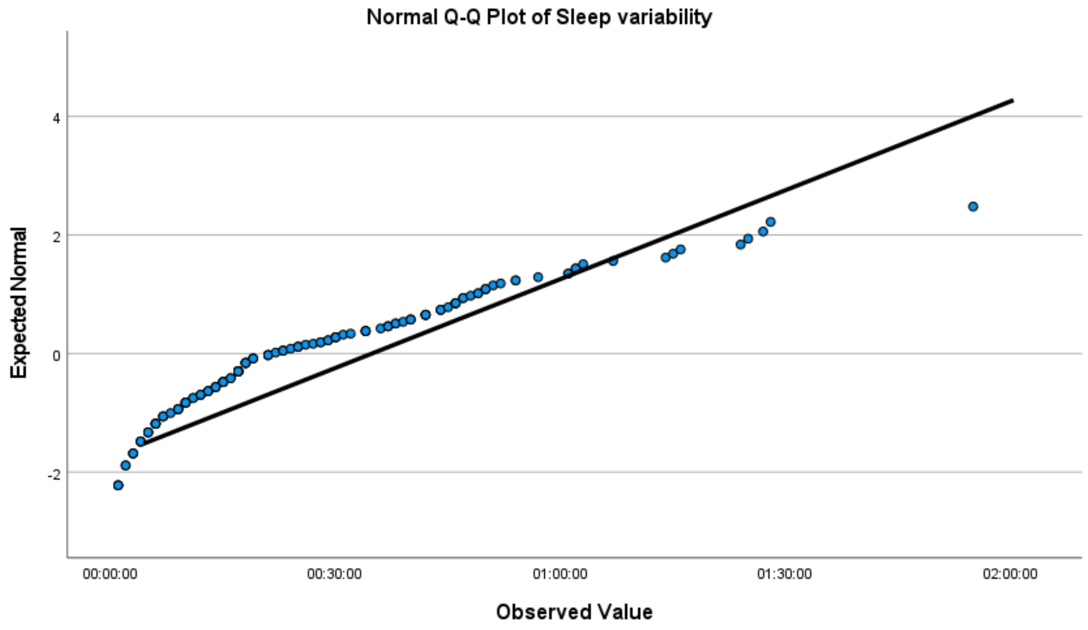
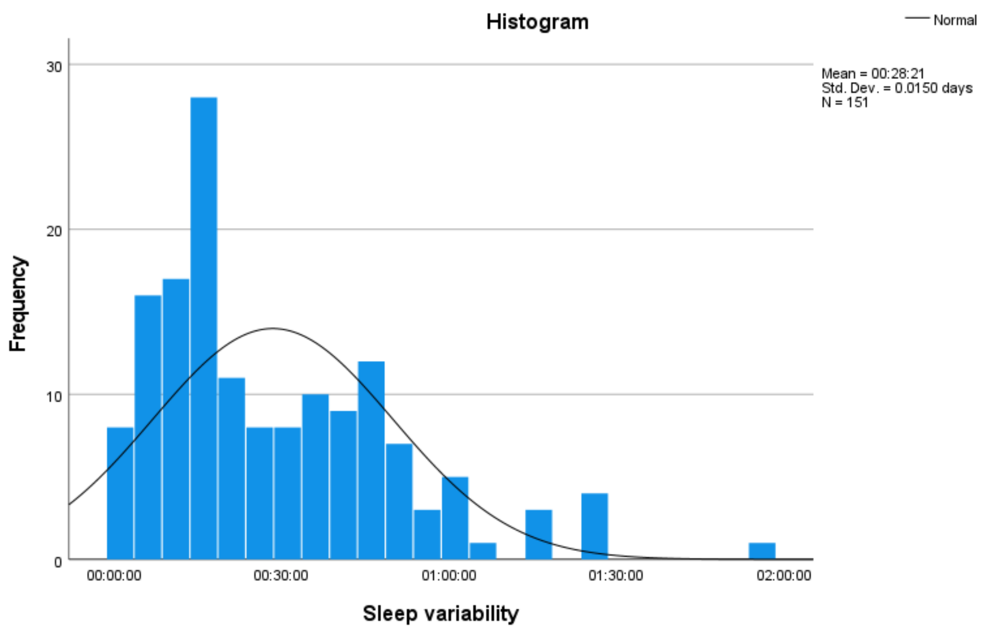


Figure B4

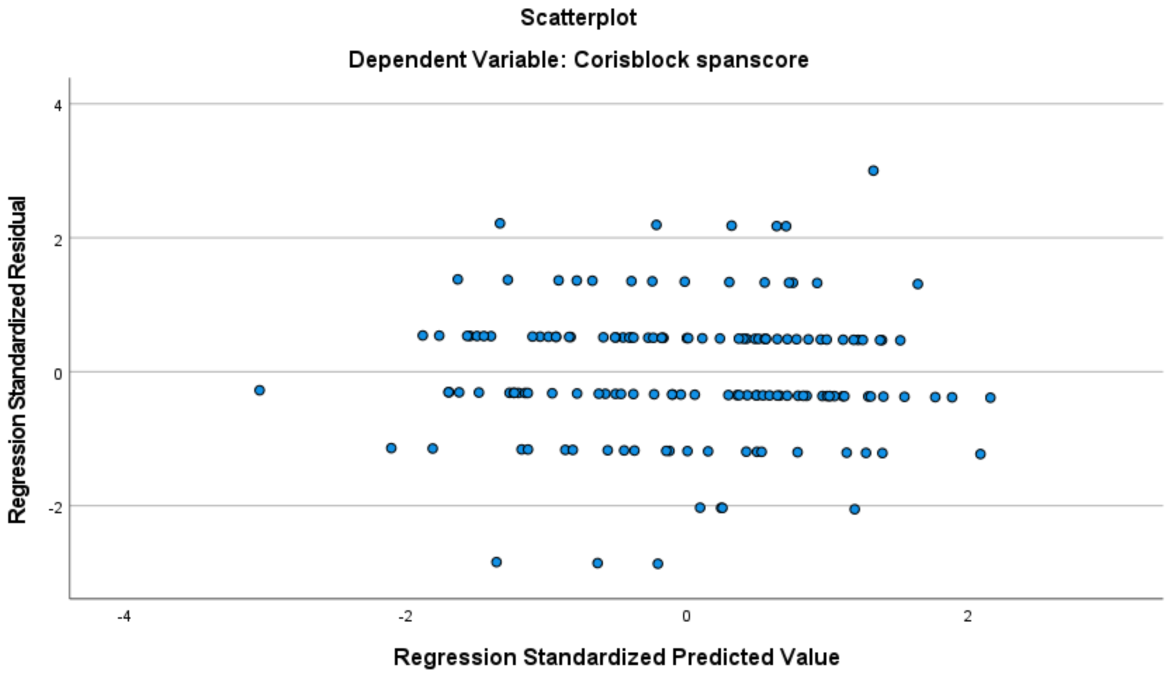
Histogram of Sleep variability



The scatterplot of standardized residuals against standardized predicted values, figure B5, shows the absence of clear patterns in the spread of points. This indicates that the assumptions linearity and homoscedasticity have not been violated.

Figure B5

Scatterplot of standardized residuals against standardized predicted values



Appendix C

The assumptions for simple linear regression for Corsiblock spanscore, sleep duration average and sleep duration night before testing are worked out below. The number of participants was 99.

The first assumption was to check for normality. A normal Q-Q plot and histogram was created for each variable individually. Figure C1 and C2 show that for Corsiblock spanscore the data is normally distributed

Figure C1

Normal Q-Q plot of Corsiblock spanscore

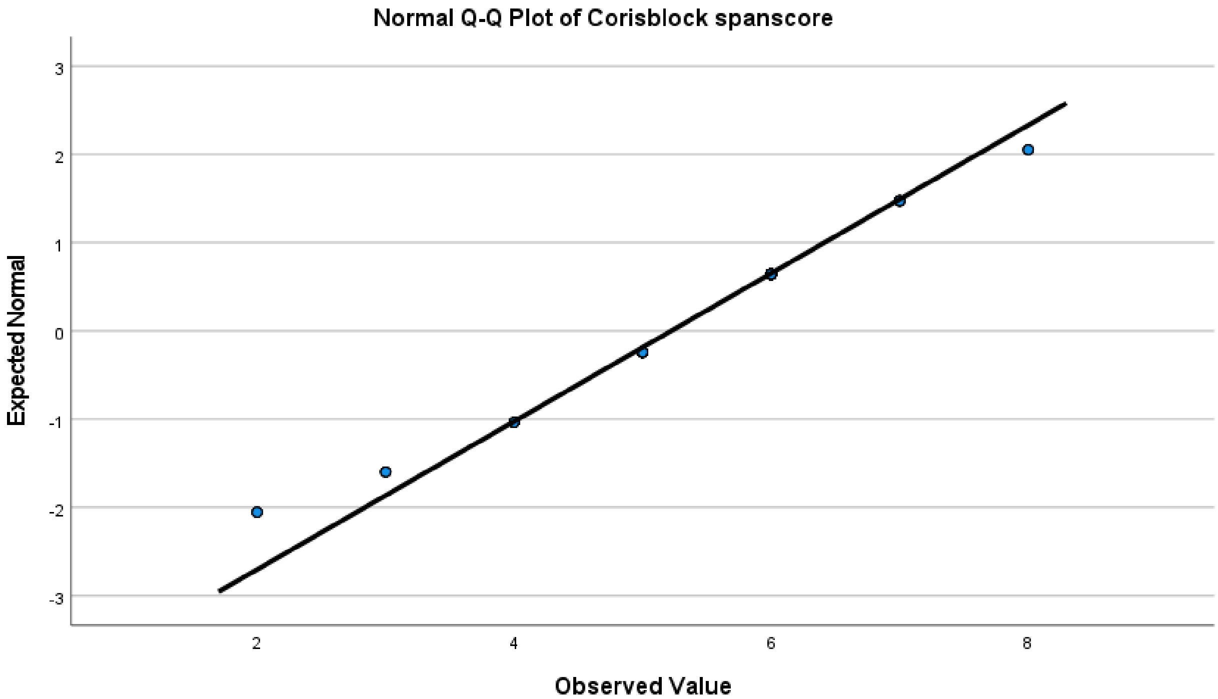


Figure C2

Histogram of Corsiblock spanscore

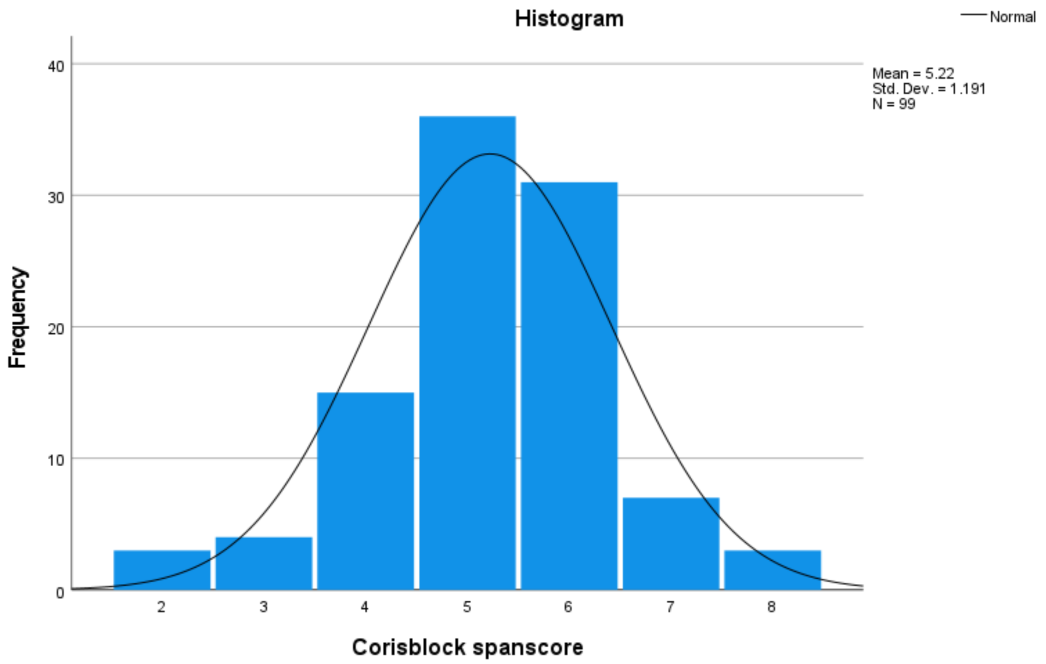


Figure C3 and C4 show the normal distribution for sleep duration average.

Figure C3

Normal Q-Q plot of Sleep duration average

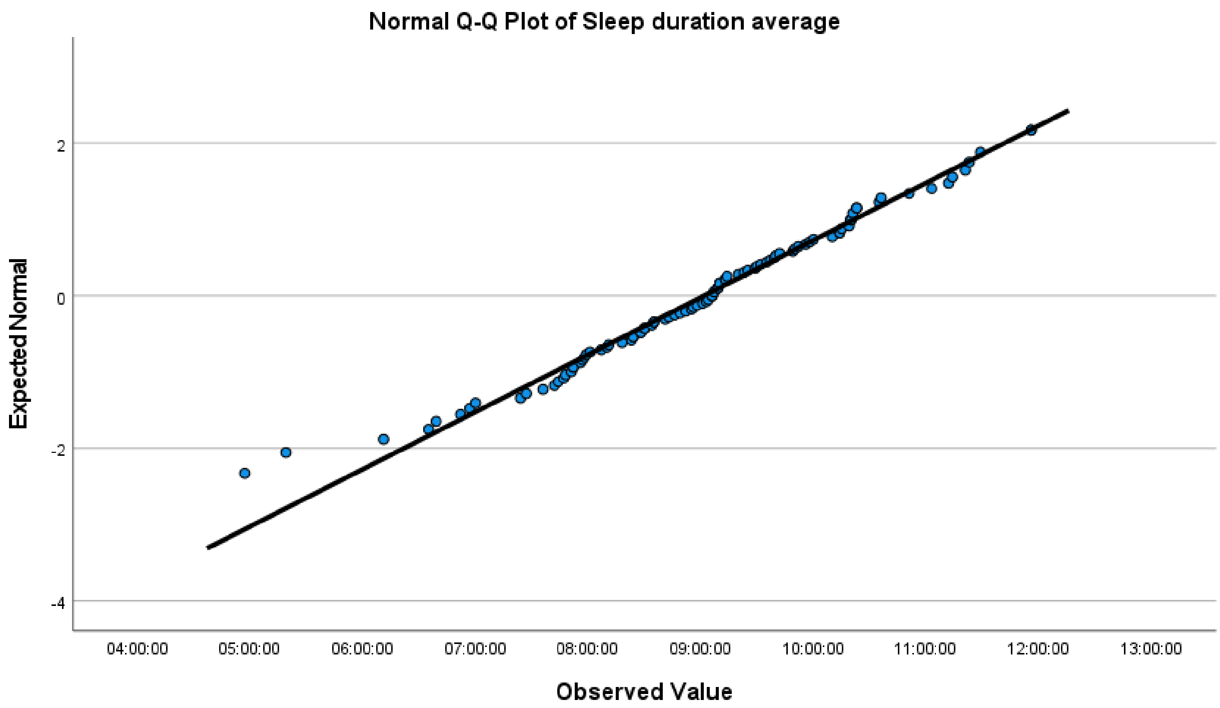


Figure C4

Histogram of Sleep duration average

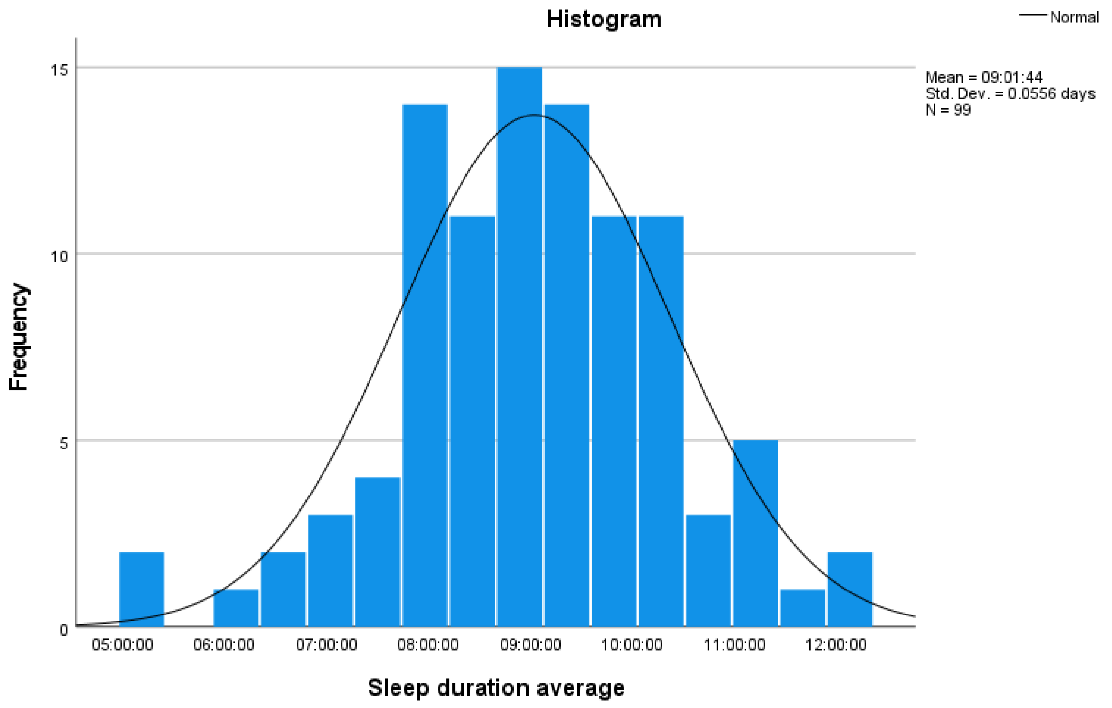


Figure C5 and C6 show the normal distribution for sleep duration the night before testing

Figure C5

Normal Q-Q plot of Sleep duration night before testing

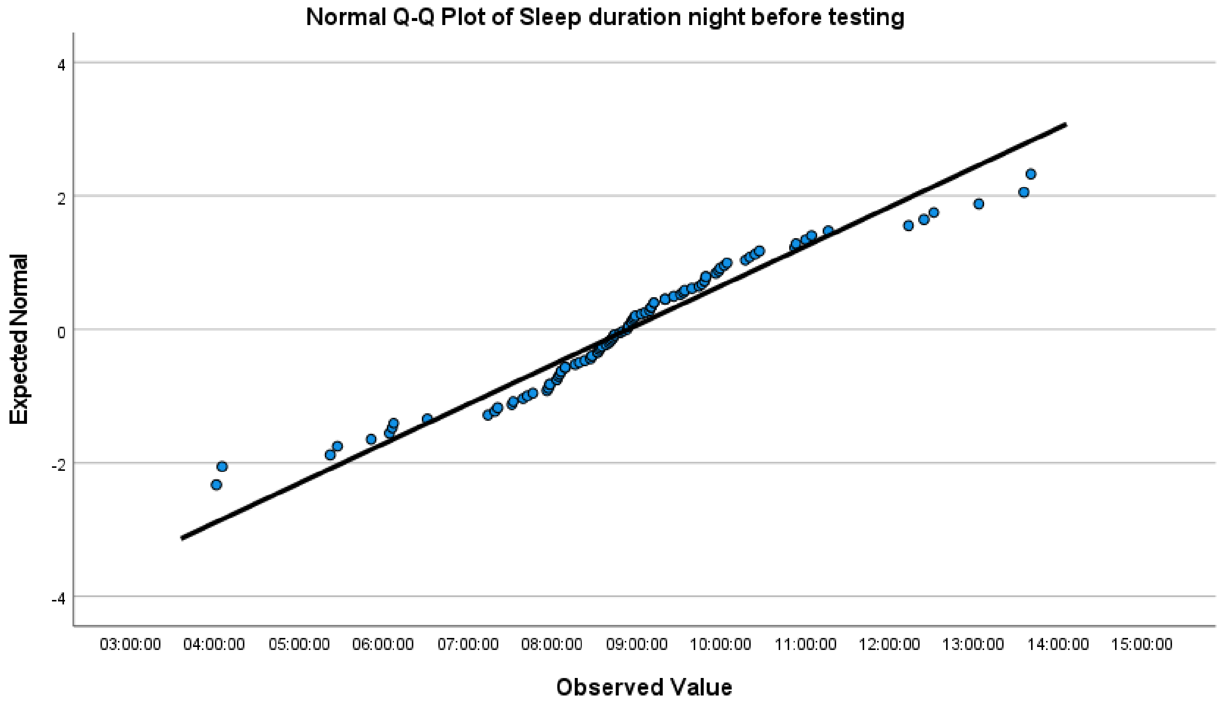


Figure C6

Histogram of Sleep duration night before testing

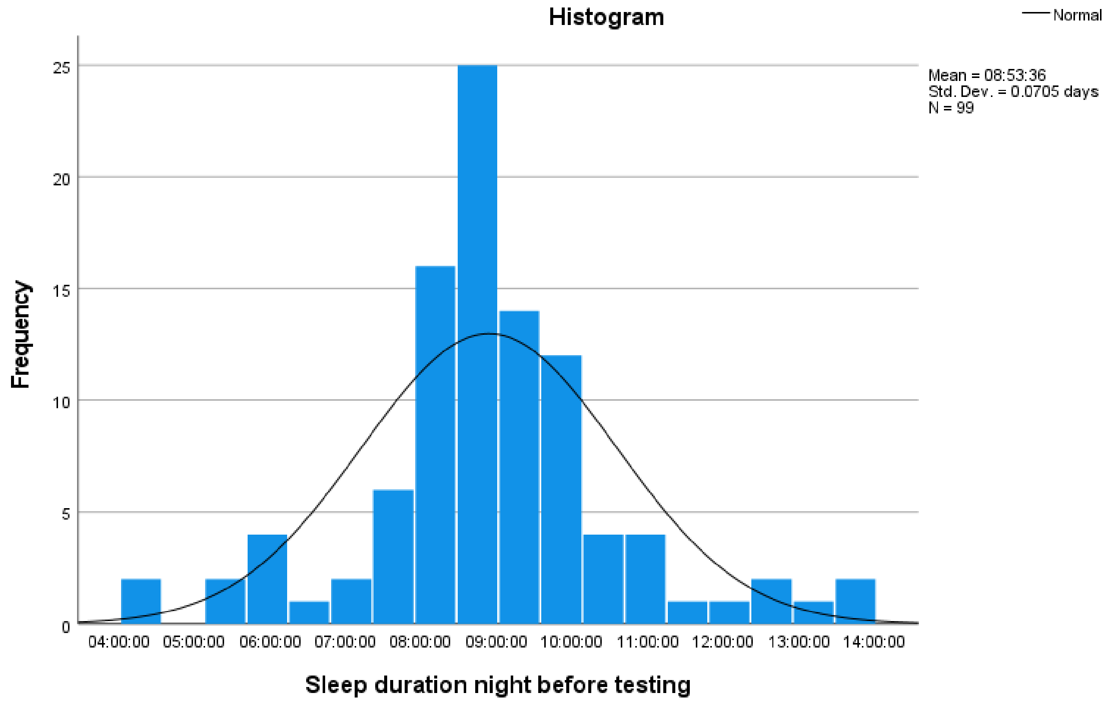


Figure C7 and C8 were used to test the linearity and homoscedasticity assumptions.

Figure C7

Scatterplot of Sleep duration night before testing and Corsiblock spanscore

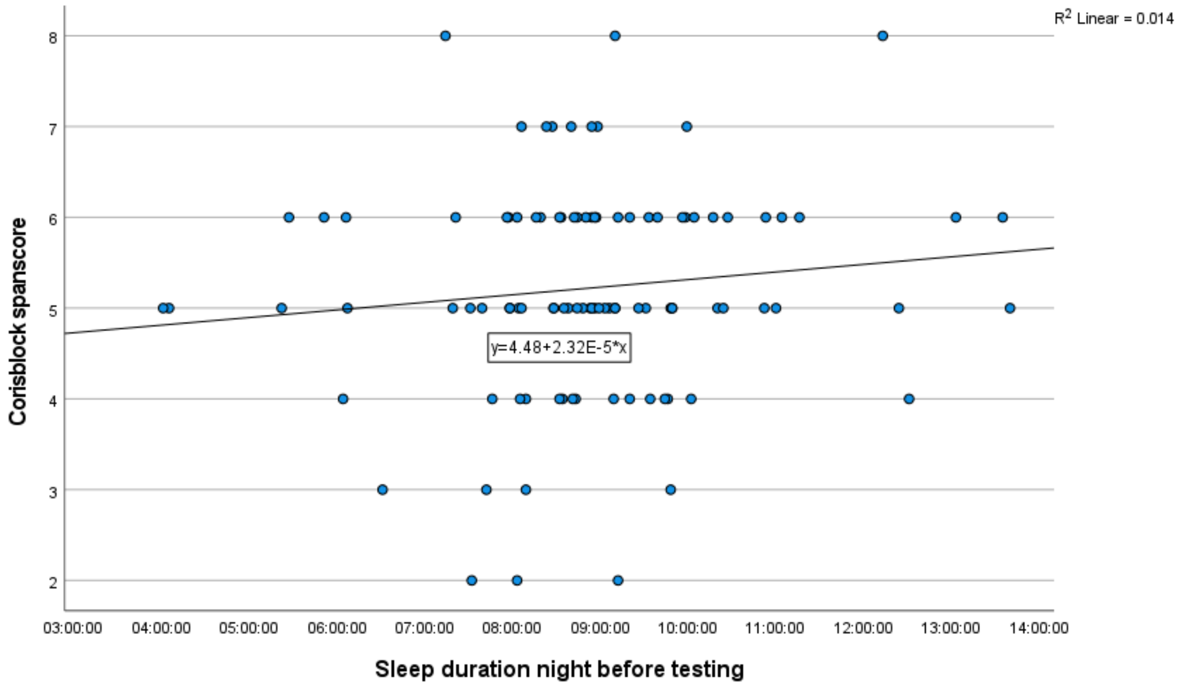


Figure C8

Scatterplot of Sleep duration average and Corsiblock spanscore