**Methods**

The current data were collected as part of a larger research project EEG Post-Covid (EPOC), which investigates neurophysiological parameters identified from neuropsychological paradigms using a high-resolution stationary laboratory EEG to reflect cognitive impairments and fatigue. The primary goal of the EPOC study is to find EEG parameters that can serve as neurophysiological markers for progression- and therapy-evaluation concerning cognitive functions in PCS.

**Participants**

Participants for the EPOC study were recruited from COVIDOM, a population-based, prospective multi-centre study to investigate PCS within the German National Pandemic Cohort Network (NAPKON). COVIDOM participants had been recruited through public health authorities and were assessed between November 15, 2020, and September 19, 2021, at University Medical Center Schleswig-Holstein, Campus Kiel, and University Hospital Würzburg in Germany (Bahmer et al., 2022; Horn et al., 2021; Schons et al., 2022). Inclusion criterias for the COVIDOM study were: A polymerase chain reaction (PCR) confirmed SARS-CoV-2 infection at least 6 months before study visit, a primary residence in one of the three study regions, age ≥ 18 years at the time of recruitment (Berlin) or infection (Würzburg, Kiel). Participants with acute reinfection of SARS-CoV-2 at the time of the scheduled study visit were excluded (Horn et al., 2021).

In the EPOC study, a subset of individuals from Schleswig-Holstein who participated in COVIDOM was selected. Prior to participation in the EPOC, participants were asked wether they experienced ongoing cognitive difficulties as a long-term symptom of their SARS-CoV-2 infection. Based on they respons, they were assigned to either the “self-reported CD” group or the “no self-reported CD” group. No other factors were relevant for grouping.

As EPOC is still ongoing at the time of writing, the analysis was conducted based on a preliminary subset of 79 participants. The study was conducted at the University Medical Center Schleswig-Holstein (UKSH), Campus Kiel. Participants did not receive payment/financial compensation for their participation. Transportation and parking costs were reimbursed.

**Ethics statement**

The study was approved by the Ethics Committee of the medical faculty of the Christian-Albrechts-University of Kiel, Germany (record identification: D 446/23). In accordance with the Declaration of Helsinki, informed written consent was obtained from all participants.

**Study design**

Participants first filled out a questionnaire on demographic data (e.g. age, education) and psychological and neurological conditions, followed by neuropsychological testing to assess cognitive domains such as working memory, attention, preprocessing speed, cognitive flexibility, executive functions, and multisensory integration. The first test administered was the Trial Marking Test (TMT). Following this, participants were seated comfortabely infront of a 27-inch screen. The EEG cap was placed, and participants were instructed to minimize movement. Electroencephalographic activity was recorded continuously while

participants completed a series of additional neuropsychological tests, starting with the redundant target effect (RTE), followed by an auditory oddball paradigm, an n-back task, and lastly the psychomotor vigilance task (PVT). Finally, resting state activity was recorded for five minutes with eyes open and five minutes with eyes closed. During eyes-open condition, participants were instructed to keep their gaze on a fixation cross displayed on the screen to reduce eye movement. An auditory signal at the end of the eyes open recording cued participants to close their eyes. There was a short pause between each measurement during which participants received instructions for the upcoming task. The light was turned off during task execution. After completing the resting state measurement, the EEG cap was removed, and participants filled out three questionnaires assessing fatigue (FACIT-F), sleep quality (PSQI), depression (HADS-D), and anxiety (HADS-A). In all, the experiment took up to 3 hours.

Since this thesis focuses on behavioral data obtained from the TMT, n-back and PVT, as well as rsEEG data, and data from the questionnaires, the RTE, and the oddball task will not be further explained. In addition, the MoCA score was measured in the previous COVIDOM study.

**Objective cognitive assessment**

**MoCA**

The Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005) is a widely used, validated screening tool originally designed to detect mild cognitive impairment (MCI) and dementia. It assesses several cognitive domains, including visuospatial skills, executive function, naming, memory, attention and concentration, language, abstraction, calculation and orientation (Freitas, Simões, Alves & Santana, 2013; Hobson, 2015; Kang et al., 2018; Nasreddine et al., 2005). The MoCA has a total possible score of 30 points, with a score of ≥ 26 considered normal (Nasreddine et al., 2005). Cognitive performance on the MoCA is influenced by sociodemographic factors such as age and education (Kang et al., 2018; Larouche et al., 2016). To account for educational background the MoCA test manual specifies that one additional point is added for individual with ≤ 12 years of formal education, allowing for a maximum score of 30 points (Nasreddine et al., 2005). Additionally, to address variations in performance related to age, normative data for the MoCA for individuals ≥ 65 years are available for precise interpretation of scores (Larouche et al., 2016).

**TMT Part A and B**

Originally, developed as part of the Army Individual Test Battery (AITB) in 1944, the Trail Marking Test (TMT) was later integrated into the Halstead-Reitan Battery (Reitan & Wolfson, 1985; Tombaugh, 2004). It is now one of the most popular and widely used neuropsychological assessments, included in most test batteries (Tombaugh, 2004). Its widespread use is supported by strong evidence of its validity (Arbuthnott & Frank, 2000; Sánchez-Cubillo et al., 2009). The TMT assesses cognitive processing speed and executive functioning (Lezak, 1995; Mitrushina et al., 2005; Sánchez-Cubillo et al., 2009; Strauss et al., 2016; Tombaugh, 2004), as well as visual search, and mental flexibility (Sánchez-Cubillo et al., 2009; Tombaugh, 2004).

The TMT consists of two parts: Part A (TMT-A), a number-connection task, and Part B (TMT-B), a number-letter alternation task. Both parts were administered according to the guidelines provided by Strauss et al. (2006).

In TMT-A, participants were instructed to connect consecutively numbered circles from 1 to 25 on an A4 page by drawing lines between them with a pencil, aiming to complete the task as quickly and accurately as possible. In TMT-B, the task becomes more complex (Gaudino, Geisler & Squires, 1995). Participants were instructed to draw lines alternating between numbered circles from 1 to 13 and lettered circles from A to L in sequential order (e.g, 1 to A, to 2, to B, etc.) on an A4 page. The aim, again, was to complete the task as quickly and accurately as possible.

The administration of the TMT began with TMT-A, followed by TMT-B. For each part, participants were first given an example to familiarize themselves with the task. After completing the example, they proceeded to the actual test. If participants made a mistake, the experimenter immediately pointed it out, and the participant was required to correct it before continuing. The experimenter timed each part, with the time of completion for each part representing its direct score. In addition to the direct scores, the difference between TMT-B and TMT-A (TMT-B – TMT-A) was calculated.

**N-Back task**

The n-back task (Kirchner, 1958) has become a widely used tool in neuroscience for assessing working memory (Jaeggi, Buschkuehl, Perrig & Meier, 2010; Pelegrina et al., 2015). N-back tasks are continuous-recognition measures, that present sequences of stimuli (Kane, Conway, Miura & Colflesh, 2007). In these tasks, participants must determine whether a given stimulus matches one that was presented “n” trials before. Reliability of the n-back task varies across studies, with more complex levels (e.g., 2-back, 3-back) generally yielding higher reliability coefficients (Jaeggi et al., 2010; Pelegrina et al., 2015).

In this study, participants completed two blocks of the n-back task: A 1-back task followed by a 2-back task, with a pause between blocks during which the instructor provided additional instructions before participants proceeded to the second block. The task was programmed in PsychoPy and presented on a 27-inch computer screen.

In both conditions, participants were shown a series of 60 linguistic stimuli, consisting of 16 different consonants (**B, C, D, F, G, H, J, K, M, Q, R, S, T, V, X, Z**) presented individually in the center of the screen. Each block contained 20 target trials and 40 non-target trials. A trial began with a 250 ms fixation period (a red dot was shown on screen, for the participant to fixate), followed by a 150 ms black screen. The stimulus letter then appeared for 500 ms, succeeded by a variable inter-trial interval of 180 to 220 ms (black screen). Total trial duration ranged from 1080 to 1120 ms.

For the 1-back task, participants were instructed to press the spacebar when the current letter matched the previous one. For example, in the sequence “B, C, C, D,” participants were supposed to respond to the second “C” as it matches the previous letter. In the 2-back task, they were instructed to press the spacebar when the current letter matched the letter presented two trials prior. For instance, in the sequence “B, B, D, F, D,” participants should press the spacebar when the second “D” occurred, as it matches the letter presented two trials before. The response window was limited to the 500 ms stimulus presentation period. Reaction time, hits, misses, and false alarms were recorded. In total, the experiment took around five minutes.

**PVT**

The Psychomotor Vigilance Task (PVT) is a widely used reaction time task developed in 1985 to assess sustained attention, particularly in contexts involving fatigue and sleep deprivation (Drummond et al., 2005). It has been shown to be sensitive to sleepiness in clinical and experimental settings (Molina, Sanabria, Jung & Correa, 2019).

The key feature of the PVT is its monotonous and unpredictable target presentation which makes participants highly prone to lapses of attention. This unpredictability minimizes learning effects, ensuring that performance remains largely independent of prior abilities and experience (Basner & Dinges, 2011). Reaction time measured by the PVT has been linked to cognitive function in both healthy subjects and patients, supporting its validity as an assessment tool (Jakobsen, Sorensen, Rask, Jensen & Kondrup, 2011).

This study employed a 5-minute version of the PVT, which has been established as a valid alternative to the traditional 10-minute PVT-192 (Lamond et al., 2008).

The dynamic stimulus appeared as a red number, counting up in milliseconds, representing the participant’s reaction time. Participants were instructed to respond immediately, when the stimulus occurred, by pressing the spacebar. Between trials, a white fixation cross was displayed on a black screen for a variable interval ranging from 2 to 10 seconds. Participants were required to maintain their gaze on this fixation cross. Each trial concluded when a response was made. Following each response, the participant’s reaction time was displayed on the screen for 500 ms as feedback before the next trial began.

After receiving instructions, participants underwent a training block of 8 trials to familiarize themselves with the task. Following the training, participants proceeded to the main experiment, which consisted of 50 stimulus presentations.

**Questionnaires**

**PSQI**

The Pittsburgh Sleep Quality Index (PSQI), developed by Buysse, Reynolds, Monk, Berman, and Kupfer in 1989 is a self-rated questionnaire that assesses sleep quality and disturbance over the past month. The PSQI is the most commonly used sleep health assessment tool in both clinical and research settings (Manzar et al., 2016). Its reliability and validity have been consistently demonstrated in multiple studies (Carpenter & Andrykowski, 1998; Manzar et al., 2018; Mollayeva et al., 2016). The questionnaire consists of 24 items in total, 19 of which are self-reported by the patient and 5 of which require input from a room or bed partner. Only the 19 self-reported items are used for the quantitative evaluation of sleep quality, as perceived by the patient (Buysse et al., 1989; Manzar et al., 2018). The response formats across the items vary, including the recording of usual bed and wake times, number of hours slept, minutes taken to fall asleep, as well as forced-choice Likert-type responses (Buysse et al., 1989). The items are categorized into seven components, which are sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbance, use of sleeping medications, and daytime dysfunction, for each component given a score. Together, these component scores generate a global sleep quality score ranging from 0 to 21, with scores >5 indicating poor sleep quality (Buysse et al., 1989; Hinz et al., 2017).

**HADS**

The self-assessment Hospital Anxiety and Depression Scale (HADS) was originally developed by Zigmond & Snaith in 1983 to identify the presence of anxiety and depression states among patients in non-psychiatric hospital clinics. HADS is an extensively used, reliable, and valid instrument to measure anxiety and depression, not only in psychiatric, and clinical patients (Herrmann, 1997) but in general populations (Bjelland, Dahl, Haug & Neckelmann, 2002; Herrero et al., 2003; Spinhoven et al., 1997). The questionnaire assesses anxiety and depression symptoms during the past week, excluding symptoms also related to physical disorders, e.g., headache, dizziness, or insomnia (Bjelland et al., 2002; Hinz & Braehler, 2011; Zigmond & Snaith, 1983). The scale consists of 14 items, divided into a 7-item anxiety (HADS-A), and a 7-item depression subscale (HADS-D). Both subscales are rated on a four-point Likert scale, giving subscale scores ranging from 0 to 21 (Zigmond & Snaith, 1983). There is no universally accepted cut-off score for the HADS (Herrero et al., 2003; Spinhoven et al., 1997). In this study, the cut-off point was set to eight, indicating caseness anxiety and depression for scores ≥8, following the recommendations by Zigmond and Snaith (1983), as well as Bjelland et al. (2002) and Herrero et al. (2003).

**FACIT-F**

The 13-item Functional Assessment of Chronic Illness Therapy - Fatigue Scale (FACIT-F) was used to assess self-reported fatigue and its impact on daily activities and functions (Cella, Lai, Chang, Peterman & Slavin, 2002; Yellen et al., 1997) during the last 7 days. While it was originally developed for cancer-related fatigue (Cella et al., 2002; Yellen et al., 1997), it has been shown, that the FACIT-F is a reliable and valid measure of fatigue across various health conditions (Cella et al., 2002), making it a widely used tool for both clinical practice and research (Cella et al., 2022; Butt et al., 2013; Montan, Löwe, Cella, Mehnert & Hinz, 2018; Tinsley, Macklin, Korzenik & Sands, 2011). This questionnaire utilizes a five-point Likert scale, with total scores ranging from 0 (severe fatigue) to 52 (no fatigue). Based on general population data, scores ≤30 indicate clinically significant fatigue (Piper & Cella, 2010).

**Statistical Analysis**

R (version 2024.4.2.764; Posit team, 2024)

**Cluster Analysis**

To classify individuals into groups based on objective cognitive assessment, a cluster analysis was conducted. The cluster analysis is an exploratory statistical method that organizes objects, data points, or observations into homogeneous groups, known as clusters, based on similarities (Ketchen & Shook, 1996). The objective is to maximize intragroup homogeneity while ensuring high intergroup heterogeneity (Bacher, Pöge & Wenzig, 2010; Backhaus, Erichson, Gensler, Weiber & Weiber, 2011). Cluster analysis does not follow a straightforward, single-step procedure but rather involves a multi-stage process, with each step depending on the outcome of the previous one (Bacher & Wenzig, 2010). Consequently, the analysis and interpretation of results may require revisiting certain steps, particularly when the initial outcomes do not allow for a meaningful interpretation (Backhaus et al., 2011). The goal was to identify the best possible solution for the dataset.

Ward’s method was selected for clustering, as it is widely used in practice and known for its effectiveness in identifying distinct clusters (Backhaus et al., 2011) with squared Euclidean distance as distance matrix. It is considered a reliable algorithm, provided that the variables are on a metric scale, are uncorrelated, and do not contain outliers (Wentura & Pospeschill, 2015).

Before the initial clustering, data were preprocessed to meet the methodological requirements of the algorithm. The MoCA variable was converted to a binary variable, with scores ≤25 indicating cognitive impairment, as the test is designed to screen for impairment without assessing severity (Nasreddine et al., 2005) For the n-back task, missing values were assigned if a participant reported not understanding the task. To ensure complete cases for analysis, rows with missing values in relevant cognitive variables were removed.

Addressing outliers was essential, as they can significantly impact the result by distorting the clustering process, obscuring underlying patterns, and introducing bias (Backhaus et al., 2011; Wentura & Pospeschill, 2015). To mitigate these effects, winsorizing was applied, to replace outliers by capping extreme values beyond 1.5 times the interquartile range (IQR) for the relevant cognitive variables (). In total, four outliers were detected and winsorized for PVT reaction time, two for TMT-A time, and four for TMT-B time.

Where appropriate, age adjustment of neurocognitive data was performed in a way that best reflected the sample distribution (Apendix), under the assumption that cognitive performance decline with increasing age (Tombaught, 2004; Strauss, Sherman & Spreen, 2006). Subsequently, data were standardized (z-scores) allowing for comparison between measures and to ensure that each variable contributed equally to the distance measure. Exploratively, different combinations of variables were tested to identify those that best distinguish between levels of cognitive performance. The number of clusters was choosen based on visual inspection of the dendrogram.

**EEG Recording and Analysis**

For each participant 5 minutes of resting state with eyes open and 5 minutes of resting state with eyes closed were recorded using high-density EEG. Since the eyes-closed condition represents a simple, standardized procedure (Babiloni et al., 2016), it is the most commonly used (Babiloni et al., 2022) and will therefore be analyzed in this study to ensure comparability. EEG signals were recorded using a 128-channel EEG cap (128Ch Standard Brain Cap for actiCHamp Plus, Easycap GmbH, Wörthsee, Germany) with electrodes positioned in an equidistant layout, connected to an actiCHamp Plus Amplifier (Brain Products GmbH, Gilching, Germany).

The sampling rate was 1000 Hz with an amplitude resolution of 0.1 µV. Electrolyte gel was applied to improve conductivity between skin and electrodes, ensuring impedances remained below 20 kΩ. Eye movements and changes in the resting potential of the retina (EOG activity) were monitored using two EOG electrodes placed below each eye, with impedances tried to maintained below 20 kΩ. In addition, a ground electrode was positioned on the forehead, and a reference electrode was positioned on the tip of the nose. Impedances for both the reference and ground electrode were tried to kept below 5 kΩ.

**Preprocessing**

Data preprocessing was performed using the FieldTrip toolbox (Fieldtrip-20240504; Oostenveld, Fries, Maris & Schoffelen, 2011) and the EEGLab toolbox (v2024.0; Delorme & Makeig, 2004) in Matlab (v24.1.0.2578822 (R2024a) Mathworks Inc., 2024, MathWorks® https://de.mathworks.com) on Windows.

**Filtering and Resampling**

A finite impulse response (FIR) windowed-sinc (firws) filter, designed with a hamming windowed sinc function, was used for both high-pass and low-pass filtering of the continuous data. For high-pass filtering, a cut-off frequency of 0.1 Hz was applied to eliminate slow drift and offset effects (Keil et al., 2013). This cut-off was based on the findings of Delorme (2023) and Winkler, Debener, Müller and Tangermann (2015), where filtering at 0.1 Hz or higher significantly improved data quality compared to no filtering.

Prior to applying low-pass filtering, the data was downsampled from 1000 Hz to 250 Hz, to reduce computational load while preserving sufficient temporal resolution for subsequent analysis. A cut-off frequency of 45 Hz was then used to eliminate high-frequency noise and mitigate potential 50 Hz line noise (Delorme, 2023). Finally, the data underwent re-referencing using the Common Average Reference (CAR) technique to remove the influence of the reference and improve signal quality (Ludwig et al., 2009). As the name implies, an average of the recordings from all electrode sites was computed and used as the reference (Ludwig et al., 2009; Offner, 1950).

**Artifact removal**

After the initial filtering and resampling, artifacts were detected and removed. First, large artifacts were removed from the data. Channels with flat lines for more than 5 seconds were removed. This ensured the exclusion of “dead” or disconnected channels, thereby improving data quality (Pernet et al., 2021). Channels were further excluded if their signal could not be predicted from a randomly selected subset of the remaining channels for at least 85% of the recording time, to remove those that were highly dissimilar from the rest of the channels (Gil Ávila et al., 2023; Pernet et al., 2021). The Euclidean distance metric was used to calculate the similarity between channels. Data segments with abnormally high amplitude bursts, exceeding 100 SD compared to neighboring segments, were eliminated, as such extreme bursts are considered unlikely to reflect brain signals (Chang et al., 2018). The default BurstCriterion is set to 20, but it may be adjusted if the default setting results in rejecting too many data segments. Some scientist recommend setting the threshold to 100 (EEGLAB, "Automated Pipeline Tutorial", 2024), which aligns with the optimal cut-off range of 10 to 100 suggested by Chang et al. (2018). Therefore, a mild threshold of 100 was chosen here, as it still effectively removes large-amplitude artifacts while retaining valuable data (Chang et al., 2018). Time windows where more than 40% of the channels were marked as noisy were removed, to ensure the quality of the remaining data. A more lenient threshold of 0.4 was chosen over the default of 0.25 to retain more data (even if it is potentially noisier).

Again the data was re-referenced to the average reference (CAR) (Gil Ávila et al., 2023).

Secondly, Independent Component Analysis (ICA) (Bell and Sejnowski, 1995; Hyvärinen, 2013, Jung et al., 2000; Lee et al., 1999; Palmer et al., 2008) was performed on the data, to detect and reject further artifacts, such as eye or muscle movements (Makeig et al., 1995). ICA with the runica algorithm was employed with the extended InfoMax method. To avoid rank deficiency, the number of components was set to one less than the total number of channels (Kim, Luo, Chu, Cannard, Hoffman & Miyakoshi, 2023). This approach decomposes the EEG signal into independent components, potentially separating artifacts from neural activity. Due to the non-deterministic nature of the ICA algorithm, its results vary across repetitions (Gil Ávila et al., 2023).

Automatic component rejection was implemented using ICALabel (Pion-Tonachini, Kreutz-Delgado & Makeig, 2019), as automatic artifact rejection is preferred over the manual one to ensure standardization (Miljevic et al., 2022). Artifactual components are automatically classified by the ICLabel classifier (Pion-Tonachini et al., 2019). Thresholds were set at probabilities of 0.8 (80%) for muscle-related components (Pernet et al., 2021) and 0.5 (50%) for eye-related components. Components exceeding these thresholds were flagged and automatically removed. The two EOG channels (31 and 32) were removed from the dataset. The cleaned dataset was then checked for consistency.

Thirdly and finally, an additional artifacts removal step was implemented to address any remaining problematic channels. This process involved a statistical approach to identify outlier channels based on their signal characteristics. The standard deviation and mean were calculated for each channel across all time points. Then, overall mean values for these standard deviations and means were computed across all channels. Thresholds were established at 2.5 standard deviations above and below the overall mean, creating an acceptable range for channel activity. Channels with standard deviations falling outside this range were removed. This step ensures that channels with unusually high or low variability, which might represent persistent artifacts or malfunctioning electrodes, are excluded from subsequent analyses.

Channels removed in the previous step were interpolated with the default spherical splines method (Perrin, Pernier, Bertrand & Echallier, 1989), ensuring a consistent number of channels across participants (Gil Ávila et al., 2023).

**Epoch length and number**

To achieve higher resolution while maintaining an adequate trial count, the continuous EEG data for each participant were segmented into 5-second nonoverlapping epochs (Bonello, Garg, Garg & Audu, 2018).

**Power Analysis**

Preprocessed EEG data were converted from EEGLAB format to FieldTrip format. Spectral parameterization was performed using SpecParam (formerly FOOOF, Fitting Oscillations & One Over F; Donoghue et al., 2020), which is implemented in the Brainstorm Toolbox (Tadel et al., 2011) and available in FieldTrip. This approach separates the periodic and aperiodic components of the power spectrum.

Spectral analysis of relative power across the 128 scalp electrodes was conducted using FieldTrips’s multitaper spectral estimation with Hanning taper, analyzing frequencies between 0.3 and 30 Hz with a frequency resolution of 0.2 Hz. The fooof output was set to a fixed aperiodic mode.. Delta power was defined as 0.6-4 Hz, and beta power as 14-30 Hz. The summed power across all frequencies within each band was used to compute the relative power per channel.

Once the relative power per channel was computed, further analysis was performed in R (version 2024.4.2.764; Posit team, 2024) To identify and remove extreme values, an initial outlier detection was performed. For each participant, channels exceeding ±3 SD from the mean relative power were excluded. This process was applied seperately for delta power, beta power.

**Statistical Analysis**

The resulting clusters were compared across cognitive measures, demographic variables, questionnaire scores and their relative beta and delta power in rsEEG to identify emerging patterns. Particular attention was given to how the objective results of the cluster analysis aligned with or differed from self-reported CD,how associated variables help explain these findings and how rsEEG beta and delta power are related to this.

To address this, comparisons were conducted not only across clusters but also between all relevant subgroups. To ensure the validity of statistical testing, assumptions for t-tests and ANOVA were first examined. The Shapiro-Wilk test was used to assess normality, and Levene’s test was applied to evaluate the homogeneity of variances. When these assumptions were violated, the non-parametric Wilcoxon test was used. For comparisons involving more than two groups, the Kruskal-Wallis test was used to determine whether significant group differences existed in the examined variable.If significance was indicated, pairwise Wilcoxon rank-sum tests with Bonferroni correction were performed as a post-hoc analysis.To test correlations, Spearman’s rank correlation was calculated.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Age group |  | PVT (ms) | | TMT-A (s) | | TMT-B (s) | | TMT\_diff (s) | | Nback\_miss1 | | Nback\_miss2 | |
| *n* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| 18 – 34 | 12 | .3166 | .0529 | 18.2 | 3.9 | 39.94 | 11.8 | 21.73 | 9.91 | 6.75 | 4.41 | 11.25 | 4.45 |
| 35 – 49 | 19 | .3247 | .058 | 24.54 | 7.09 | 45.92 | 10.54 | 21.38 | 6.4 | 8.79 | 3.58 | 14.21 | 3.29 |
| 50 – 64 | 33 | .3278 | .0543 | 27.14 | 7.48 | 59.02 | 16.16 | 31.88 | 14.03 | 10.06 | 6.61 | 13.61 | 4.46 |
| 65 – 80 | 6 | .3337 | .0177 | 34.57 | 9.97 | 65.13 | 21.3 | 30.56 | 17.99 | 8.83 | 4.22 | 15.17 | 4.92 |