Three distinct patterns of mental response after a sport accident

Supplementary Material

Psychiatry Study Team

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# Supplementary Methods

## Software

Data analysis and transformation was accomplished with R version 4.2.0. The study dataset was imported from an SPSS file with the *foreign* package (1). Tabular data were handled with the *tidyverse* package bundle (2) and the packages *rlang* (3) and [*trafo*](https://github.com/PiotrTymoszuk/trafo). Test variables were handled with *stringi* (4).

For distribution testing (normality, variance, Gini index), the packages [*ExDA*](https://github.com/PiotrTymoszuk/ExDA), *rstatix* (5) and *DescTools* (6) were utilized. Consistency of psychometric tools was assessed with the packages *psych* (7), [*ExDA*](https://github.com/PiotrTymoszuk/ExDA) and [*clustTools*](https://github.com/PiotrTymoszuk/clustTools). Clustering tendency was investigated with *factoextra* (8) and [*clustTools*](https://github.com/PiotrTymoszuk/clustTools). Statistical hypothesis testing and correlation analyses were accomplished with [*ExDA*](https://github.com/PiotrTymoszuk/ExDA), *rstatix* (5).

For clustering, the package [*clustTools*](https://github.com/PiotrTymoszuk/clustTools) with implementation of algorithms and distance measures from *factoextra*, *cluster* and *philentropy* (8–10) was utilized. UMAP (uniform manifold approximation and projection) was done with the *umap* package (11,12). Univariable mental cluster assignment classifiers were developed with the *OneR* (13,14). A multi-variable classifier for mental cluster assignment was developed with the conditional random forest algorithm (15,16) implemented in the *party* package (17). Accuracy of the classifiers was assessed with the packages *caret* (18) and [*caretExtra*](https://github.com/PiotrTymoszuk/caretExtra).

Results were visualized with *ggplot* (bar plots, box plots and heat maps of confusion matrices) (19), [*ExDA*](https://github.com/PiotrTymoszuk/ExDA) (violin, stack and ribbon plots) and [*clustTools*](https://github.com/PiotrTymoszuk/clustTools) (cluster quality control plots, clustering features heat maps, distance heat maps, scatter plots of UMAP layouts). Figures were created with the package *cowplot* (20). Tables were generated with *flextable* (21). The manuscript and Supplementary Material were written in *rmarkdown* (22) with the package *bookdown* (23). Figures, tables and R expressions in the markdown documents were managed with the development package [*figur*](https://github.com/PiotrTymoszuk/figur). The markdown documents were rendered with *knitr* (24), *bookdown* (23) with author-info-blocks.lua and scholarly-metadata.lua scripts by Albert Krewinkel and Jörn Krenzer.

## Data import and transformation

The study data set was imported from an SPSS file with raw study data (function read.spss(), package *foreign*). The list of extracted variables with their description is available in **Supplementary Table S1**. A total of 307 participants with the complete set of psychometric battery variables (**Supplementary Table S2**) were included in the analysis (**Figure 1**).

The psychometric battery (**Supplementary Table S2**) consisted of German versions of assessment tools for anxiety (GAD-7: 7-item general anxiety disorder scale) (25), depression (PHQ: patient health questionnaire, PHQ-9) (26,27), panic (PHQ-panic module) (26,27), persistent somatic symptoms (PHQ-15) (28), resilient coping (RS13: 13-item resilience scale) (29), loss of sense of coherence (SOC-9L: Leipzig 9-item sense of coherence questionnaire) (30), loss of quality of life (EUROHIS-QOL 8: 8-item EUROHIS project quality of life scale) (31), post-traumatic growth (PTGI: post-traumatic growth inventory) (32) and post-traumatic syndrome disorder (PCL-5 DSM-5: PTSD checklist for DSM-5) (33).

Symptoms of anxiety were defined as GAD-7 10, symptoms of depression were defined as PHQ-9 11 (34), significant somatization/persistent somatic symptoms were defined as PHQ-15 11 (28). Resilient coping classes were defined as follows: low: RS-13 0 - 65, moderate: 66 - 72, high: 73 (29).

Items of the EUROHIS QOL 8 tool were scores as with 1 - 5 likert scales (1: no concerns/full satisfaction, 5: extreme concerns, no satisfaction at all) with each item representing a single domain of quality of life (quality of life, health, energy, finances, activity, self-esteem, relationship and housing). The total EUROHIS QOL score was defined as the arithmetic mean of all items (31).

Separate scores were computed for each domain of the PTGI tool (I: relations, II: possibilities, III: personal strength, IV: spiritual strength, V: life appreciation) with each item scores as 0: none, 1: very little, 2: little, 3: moderate, 4: great, 5: extremely great. In addition, the total PTGI score was calculated as the sum of all items (32).

Separate scores were calculated for domains B, C, D and E of the PCL-5 DSM-5 tool along with the total score being the sum of all items. Each PCL-5 DSM-5 item was scored as 0: not at all, 1: a little bit, 2: moderate, 3: quite a bit and 4: extremely. Participants positive for the B domain or C domain were identified by at least one item scored with ‘moderate’, participants positive for the D or E domain were identified by at least two item scored with ‘moderate’. Significant PTSD symptoms where assumed in participants screened positive for at least one of the B, C, D or E PCL-5 DSM-5 domains (33).

Traumatic events prior to the sport accident were assessed with the DIA-X tool (35). Direct personal experience or being a witness of a traumatic event specified by the DIA-X questionnaire or by an additional yes/no item (‘other traumatic events’) was scored as 1. Prior traumatic event was assumed with at least one DIA-X item scored with 1. Prior sport accidents, flashbacks during sport activity, confusion during sport activity, subjective need for psychological support, presence of psychological/psychiatric support/therapy post accident and presence of somatic health consequences after the accident were surveyed as single yes/no items. Flashbacks frequency was assessed in the following categories: none, more than one per month and more than one per year. Smoking was surveyed as a single yes/no question. Substance abuse was investigated with the CAGE tool with 2 points indicative of substantial addiction (36). Data on hospital treatment, hospitalization and surgery were extracted from electronic patient’s records. Injury severity was assessed with the abbreviated injury scale (AIS) (37).

Additional information on study variables and their stratification schemes are presented in **Supplementary Table S1**.

## Consistency of psychometric tools and power analysis

Consistency of psychometric tools was assessed by factor analysis and McDonald’s (function omega(), package *psych*) (7,38). The number of latent factors for calculation of was identified by inspection of loadings determined by factor analysis (function reduce\_data(), [*clustTools*](https://github.com/PiotrTymoszuk/clustTools)). All psychometric tools used in the study except for the stress PSS-4 scale (39) and the BRCS resilience tool (40) exhibited good-to-excellent consistency with > 0.8 (**Supplementary Table S3**). The poorly performing PSS-4 and BRCS scales were excluded from the further analysis.

To find the optimal size of a training subset of the study cohort, random subsamples of the study dataset of varying sizes were investigated (50, 100, 150, 200, 250, 300 observations, 50 random draws per subsample size). For each random subsample, clustering tendency was assessed by Hopkins statistic (function get\_clust\_tendency(), package [*clustTools*](https://github.com/PiotrTymoszuk/clustTools)). For n = 200 observations, the median Hopkins statistic was 0.72 (interquartile range: 0.72 - 0.73) indicative of good clustering tendency. The Hopkins statistic value for this subset was comparable with the value for the entire subset (0.74). For these reasons, 2/3 of the entire dataset or n = 204 was considered as the size of the training subset of the study cohort.

## Training/test subset definition

The study participants were assigned to the training and test subsets with the 2:1 size ratio (**Figure 1**). To this end, 1000 random splits of the datasets were generated. The subset assignment scheme was chosen with possibly small differences in accident year, age, gender, somatic and mental illness rates, frequencies of prior traumatic events (DIA-X) (35) and distribution of injury severity grades (AIS: abbreviated injury scale) (37) as investigated by and Mann-Whitney test, as appropriate (functions chisq\_test() and wilcox\_test(), package *rstatix*).

## Assessment of selection bias

To assess possible selection bias, demographic, socioeconomic, clinical and accident-related parameters were compared between individuals excluded due to missingness of psychometric data or denying survey participation and participants included in he analysis (**Figure 1**). Categorical variables were compared by test with Cramer V effect size statistic and numeric variables were compared by Mann-Whitney test with r effect size statistic (function compare\_variables(), package [*ExDA*](https://github.com/PiotrTymoszuk/ExDA)). Potential differences between the training and test subset of the study cohort (**Figure 1**) were analyzed in an analogical way. Significant and near-significant (p < 0.1) differences between the included/excluded participants and the training/test subsets are presented in **Supplementary Tables S4** and **S5**, respectively.

## Semi-supervised clustering

Observations of the training subset of the study cohort were subjected to clustering in respect to the numeric psychometric scores (**Supplementary Table S2**). The score values were normalized and median-centered (function center\_data(), package [*clustTools*](https://github.com/PiotrTymoszuk/clustTools)). For clustering, the PAM (partition around medoids) algorithm (9) with the cosine distance measure between observations (10) was employed. The clustering object was constructed with the function kcluster() from the [*clustTools*](https://github.com/PiotrTymoszuk/clustTools) package. The choice of the clustering algorithm was motivated by its good explanatory performance measured by the fraction of explained clustering variance (ratio of between-cluster sum of squares to total sum of squares, method var(), [*clustTools*](https://github.com/PiotrTymoszuk/clustTools)) and superior stability in 10-fold cross-validation (41) (cluster assignment in the folds by an inverse distance weighted 7-nearest neighbors classifier, method cv(), [*clustTools*](https://github.com/PiotrTymoszuk/clustTools)) in a comparison with several other clustering algorithms presented in **Supplementary Figure S2A**. The number of cluster was chosen based on the bend of the curve of within-cluster sum of squares and the peak of mean silhouette statistic (method plot(), package [*ExDA*](https://github.com/PiotrTymoszuk/ExDA)). By this means, three mental clusters were defined: the neutral, PTG (post-traumatic growth) and PTSD (post-traumatic syndrome disorder) clusters (**Supplementary Figure S2B**). Assignment of the training subset observations to the mental clusters was accomplished with an inverse distance weighted 7-nearest neighbor classifier. This semi-supervised procedure yielded clustering structures with similar fractions of explained variance in the training (V = 0.54) and test subset (V = 0.54). In addition, comparable separation between the clusters could be discerned in the training and test subsets by a visual analysis of UMAP layouts, pairwise distance heat maps (**Supplementary Figure S3**) and heat maps of normalized levels of the clustering variables (**Supplementary Figure S4**).

Differences in clustering variables, frequencies of mental disorder symptoms as well as demographic, socioeconomic, clinical and accident-related factors between the mental clusters were assessed separately in the training and test subset by test with Cramer V effect size statistic and Kruskal-Wallis test with effect size statistic for categorical and numeric variables, respectively (**Supplementary Tables S6** and **S7**).

## Uni- and multi-variable cluster assignment classifiers

Univariable classifiers of the mental cluster assignment for demographic, socioeconomic, clinical and accident-related parameters were trained in the training subset of the study cohort by the one-rule (oneR) algorithm (function OneR(), package \_OneR\_\_) (13,14). The cluster assignment was subsequently predicted for the test subset observations (method predict(), package *OneR*). The multi-parameter classifier was developed in the training subset with the conditional random forest algorithm (15–17) with n = 1000 random trees, the splitting rule corresponding to the maximum test statistic and five variable draws per tree (function cforest() with the cforest\_control(teststat = 'max', testtype = 'Teststatistic', mtry = 5, mincriterion = qnorm(0.9), ntree = 1000) control object, package *party*). The optimal variable draw values were obtained by optimization (tuning) employing the out-of-bag predictions in the training subsets (not shown). The cluster assignment was subsequently predicted for the test subset observations (method predict(), package *party*).

Accuracy and statistic for the classifiers’ mental cluster assignment predictions in the training and test subsets were computed with the function multiClassSummary() from the package *caret* (18). Conditional importance for explanatory variables expressed as accuracy loss (42) was obtained for the conditional random forest algorithm with the function ’varimp()` from the *party* package.

## Data and code availability

An R data (RData) file with anonymized patient data will be made available upon request to the corresponding author. The study analysis pipeline is available at <https://github.com/PiotrTymoszuk/mental_accident>.

# Supplementary Tables

Supplementary Table S1: Variables used in the analysis pipeline. The table is available in a supplementary Excel file.

Supplementary Table S2: Mental health assessment battery. The table is available in a supplementary Excel file.

Supplementary Table S3: Consistency of the psychometric tools used in the study measured by McDonald’s omega.

| **Scalea** | **Number of latent factors** | **Total omega** |
| --- | --- | --- |
| RS13 | 2 | 0.94 |
| PTGI | 2 | 0.93 |
| GAD-7 | 3 | 0.89 |
| PHQ-panic | 1 | 0.88 |
| EUROHIS-QOL 8 | 4 | 0.88 |
| PHQ-9 | 4 | 0.87 |
| PHQ-15 | 4 | 0.84 |
| PCL-5 DSM-5 | 1 | 0.81 |
| PSS4 | 1 | 0.65 |
| BRCS | 1 | 0.63 |
| aGAD-7: 7-item general anxiety disorder scale; PHQ: patient health questionnaire; EUROHIS-QOL 8: 8-item EUROHIS project quality of life scale; SOC-9L: Leipzig 9-item sense of coherence questionnaire; RS13: 13-item resilience scale; BRCS: brief resilent coping scale; PCL-5 DSM-5: PTSD checklist for DSM-5; PTGI: post-traumatic growth inventory | | |

Supplementary Table S4: Significant and near-significant (p < 0.1) differences between individuals excluded from analysis and analyzed study participants. Numeric variables are presented as medians with interquartile ranges (IQR). Categorical variables are presented as percentages and counts within the complete observation set.

| **Variable** | **Included** | **Excluded** | **Significancea** | **Effect sizea** |
| --- | --- | --- | --- | --- |
| employment | employed: 68% (n = 210) unemployed: 3.6% (n = 11) student: 10% (n = 32) retired: 18% (n = 54) n = 307 | employed: 54% (n = 43) unemployed: 5% (n = 4) student: 19% (n = 15) retired: 22% (n = 18) n = 80 | ns (p = 0.077) | V = 0.13 |
| income/year | no income: 21% (n = 63) < 30000 EUR: 18% (n = 56) 30000 - 45000 EUR: 19% (n = 59) ≥ 45000 EUR: 42% (n = 129) n = 307 | no income: 44% (n = 35) < 30000 EUR: 14% (n = 11) 30000 - 45000 EUR: 16% (n = 13) ≥ 45000 EUR: 26% (n = 21) n = 80 | p < 0.001 | V = 0.22 |
| income ≥ 45K EUR/year | 42% (n = 129) n = 307 | 26% (n = 21) n = 80 | p = 0.014 | V = 0.13 |
| somatic illness | 15% (n = 47) n = 307 | 5.3% (n = 3) n = 57 | ns (p = 0.07) | V = 0.11 |
| accident year | 2018: 69% (n = 213) 2019: 7.2% (n = 22) 2020: 23% (n = 72) n = 307 | 2018: 72% (n = 3042) 2019: 9.6% (n = 408) 2020: 19% (n = 801) n = 4251 | ns (p = 0.076) | V = 0.034 |
| sport type | ski/snowboard: 64% (n = 197) sledding: 3.9% (n = 12) mountain: 14% (n = 42) biking: 16% (n = 48) other: 2.6% (n = 8) n = 307 | ski/snowboard: 52% (n = 2224) sledding: 5% (n = 212) mountain: 11% (n = 467) biking: 27% (n = 1144) other: 4.8% (n = 205) n = 4252 | p < 0.001 | V = 0.077 |
| alone during the accident | 32% (n = 97) n = 307 | 20% (n = 14) n = 69 | ns (p = 0.086) | V = 0.096 |
| accident culpritb | self: 77% (n = 237) non-self: 23% (n = 70) n = 307 | self: 65% (n = 45) non-self: 35% (n = 24) n = 69 | ns (p = 0.054) | V = 0.11 |
| rescue | self: 50% (n = 155) partner/third party: 21% (n = 63) rescue team: 29% (n = 89) n = 307 | self: 66% (n = 42) partner/third party: 19% (n = 12) rescue team: 16% (n = 10) n = 64 | ns (p = 0.052) | V = 0.13 |
| injury severity, AIS | 1: 37% (n = 108) 2: 35% (n = 103) 3+: 28% (n = 83) 0: 0% (n = 0) n = 294 | 1: 46% (n = 156) 2: 36% (n = 121) 3+: 17% (n = 56) 0: 1.2% (n = 4) n = 337 | p < 0.001 | V = 0.16 |
| injury severity, AISc | 2 [IQR: 1 - 3], range: 1 - 5 n = 294 | 2 [IQR: 1 - 2], range: 0 - 4 n = 337 | p < 0.001 | r = 0.15 |
| upper limb injuryd | 41% (n = 120) n = 294 | 48% (n = 163) n = 337 | ns (p = 0.068) | V = 0.076 |
| hospitalizedd | 26% (n = 80) n = 307 | 9.5% (n = 404) n = 4252 | p < 0.001 | V = 0.13 |
| surgeryd | 14% (n = 43) n = 307 | 4.2% (n = 179) n = 4252 | p < 0.001 | V = 0.11 |
| surgery diagnosesd | 0 [IQR: 0 - 0], range: 0 - 9 n = 307 | 0 [IQR: 0 - 0], range: 0 - 9 n = 4252 | p < 0.001 | r = 0.11 |
| somatic accident aftermathe | 37% (n = 115) n = 307 | 22% (n = 12) n = 55 | p = 0.037 | V = 0.12 |
| PCL-5 DSM-5 scoref | 3 [IQR: 1 - 7], range: 0 - 44 n = 307 | 2 [IQR: 0 - 4.2], range: 0 - 37 n = 44 | ns (p = 0.096) | r = 0.089 |
| PTGI score | 32 [IQR: 16 - 48], range: 0 - 100 n = 307 | 8.5 [IQR: 3 - 41], range: 0 - 78 n = 18 | p = 0.026 | r = 0.12 |
| PTGI I relations score | 12 [IQR: 6 - 18], range: 0 - 35 n = 307 | 2.5 [IQR: 0 - 13], range: 0 - 28 n = 18 | p = 0.0071 | r = 0.15 |
| PTGI III personal strength score | 8 [IQR: 4 - 11], range: 0 - 20 n = 307 | 4.5 [IQR: 0 - 8.8], range: 0 - 16 n = 18 | p = 0.028 | r = 0.12 |
| PTGI V life appreciation score | 6 [IQR: 2 - 9], range: 0 - 15 n = 307 | 1.5 [IQR: 0.25 - 6.8], range: 0 - 12 n = 18 | p = 0.049 | r = 0.11 |
| SOC-9L score | 19 [IQR: 16 - 25], range: 10 - 49 n = 307 | 27 [IQR: 20 - 35], range: 17 - 50 n = 11 | p = 0.0062 | r = 0.15 |
| aNumeric variables: Mann-Whitney test with r effect size statistic; categorical variables: <² test with Cramer V effec size statistic | | | | |
| bAIS: abbreviated injury scale | | | | |
| cPCL-5 DSM-5: PTSD checklist for DSM-5 | | | | |
| dPTGI: post-traumatic growth inventory | | | | |
| ePSS4: 4-item perceived stress scale | | | | |
| fSOC-9L: Leipzig 9-item sense of coherence scale | | | | |

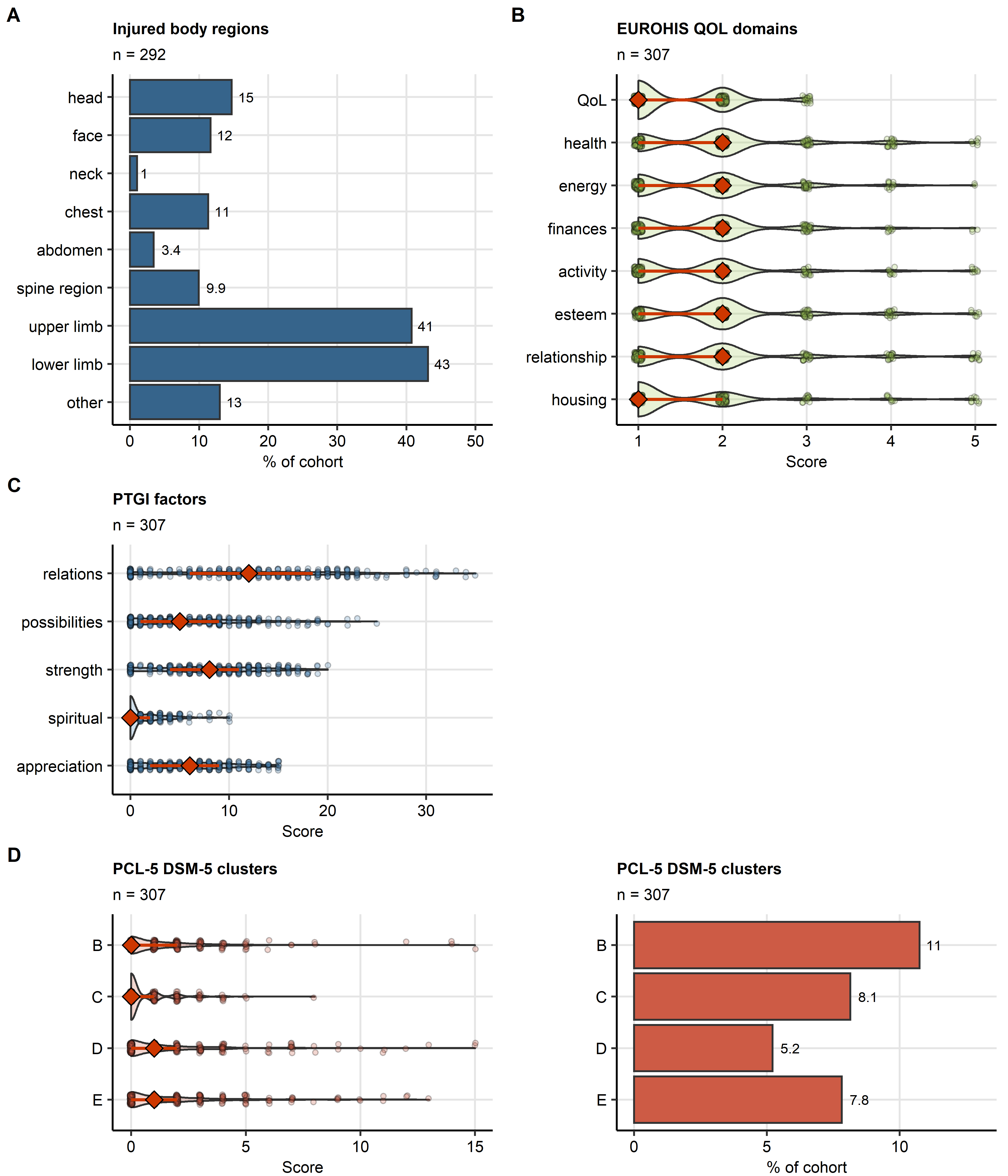
Supplementary Table S5: Significant and near-significant (p < 0.1) differences between the training and test subsets of the study cohort. Numeric variables are presented as medians with interquartile ranges (IQR). Categorical variables are presented as percentages and counts within the complete observation set.

| **Variable** | **Training** | **Test** | **Significance** | **Effect size** |
| --- | --- | --- | --- | --- |
| face injury | 14% (n = 28) n = 198 | 6.2% (n = 6) n = 96 | ns (p = 0.074)a | V = 0.12a |
| RS13 coping classb | low: 21% (n = 42) moderate: 11% (n = 22) high: 69% (n = 140) n = 204 | low: 14% (n = 14) moderate: 19% (n = 20) high: 67% (n = 69) n = 103 | ns (p = 0.061) | V = 0.14 |
| a<² test with Cramer V effec size statistic | | | | |
| bRS13: 13-item resilience scale | | | | |

Supplementary Table S6: Differences in psychometric clustering factors between the mental clusters. Numeric variables are presented as medians with interquartile ranges (IQR). The table is available in a supplementary Excel file.

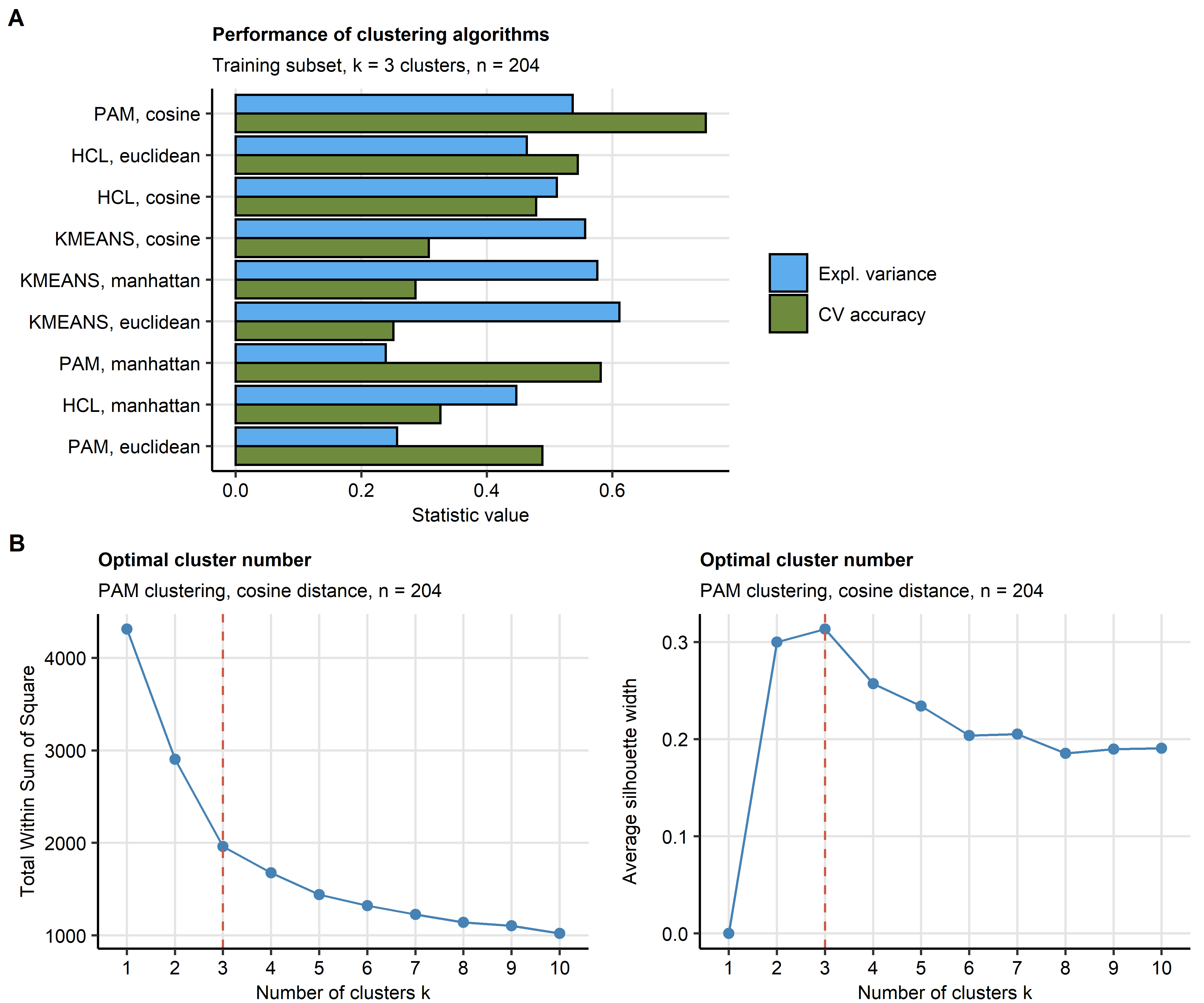
Supplementary Table S7: Significant and near-significant (p < 0.1) differences in demographic, socioeconomic, clinical and accident-related factors between the mental clusters. Numeric variables are presented as medians with interquartile ranges (IQR). Categorical variables are presented as percentages and counts within the complete observation set. The table is available in a supplementary Excel file.

# Supplementary Figures



**Supplementary Figure S1. Injured body regions and detailed scoring of quality of life, post-traumatic syndrome disorder and post-traumatic growth in the study cohort.**

*For categorical variables, percentages of complete observations are presented as bars. Numeric variables are presented in violin plots with red diamonds denoting medians, interquartile ranges presented as red whiskers and single observations depicted as points. The number of complete cases is displayed in the plot captions.* *(A) Distribution of injured body regions. (B) Scoring of the domains of the EUROHIS project 8-item quality of life scale (EUROHIS-QOL 8). (C) Scoring of the post-traumatic syndrome disorder (PTSD) clusters with the PCL-5 DSM-5 tool and percentages of participants screened positive for the PTSD clusters. (E) Scoring of the factors of the post-traumatic growth with the post-traumatic growth inventory (PTGI) tool.*

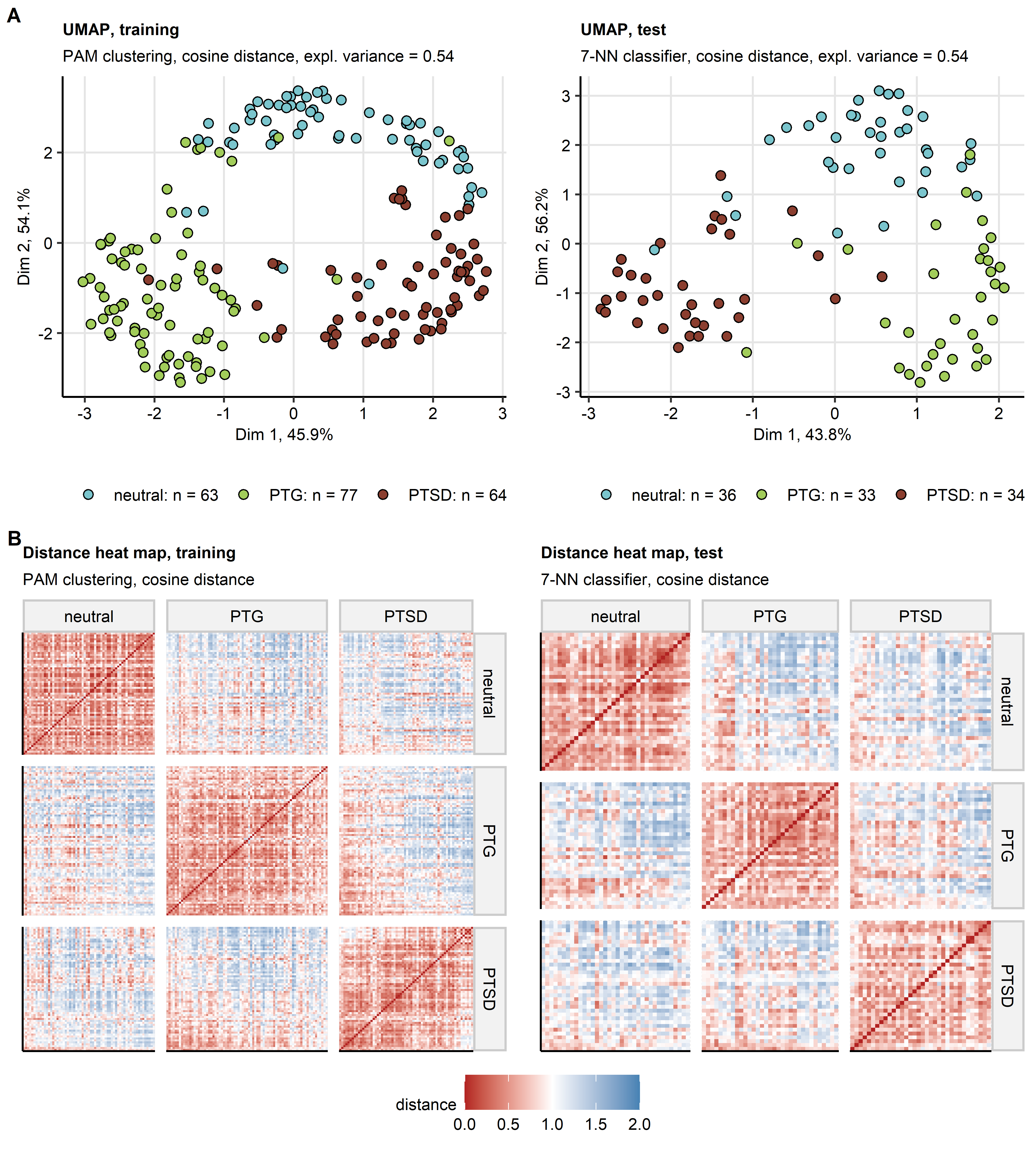


**Supplementary Figure S2. Definition of the mental clusters in the training subset of the study cohort.**

*The mental clusters were defined in respect to psychometric scoring in the training subset of the study cohort by PAM (partition around medoids) with cosine distance between the observations.*

*(A) Comparison of explanatory performance and stability of various clustering algorithms in the training subset. The explanatory performance was measured as a fraction of explained clustering variance (ratio of between-cluster sum of squares to total sum of squares). The stability was assessed by a rate of correct cluster assignment in 10-fold cross-validation (CV) with cluster assignment in the folds by an inverse distance weighted 7-nearest neighbors classifier. Note the superior stability of the PAM/cosine distance algorithm.*

*(B) Determination of the cluster number by the bend of the within-cluster sum of squares curve and the peak mean silhouette statistic.*

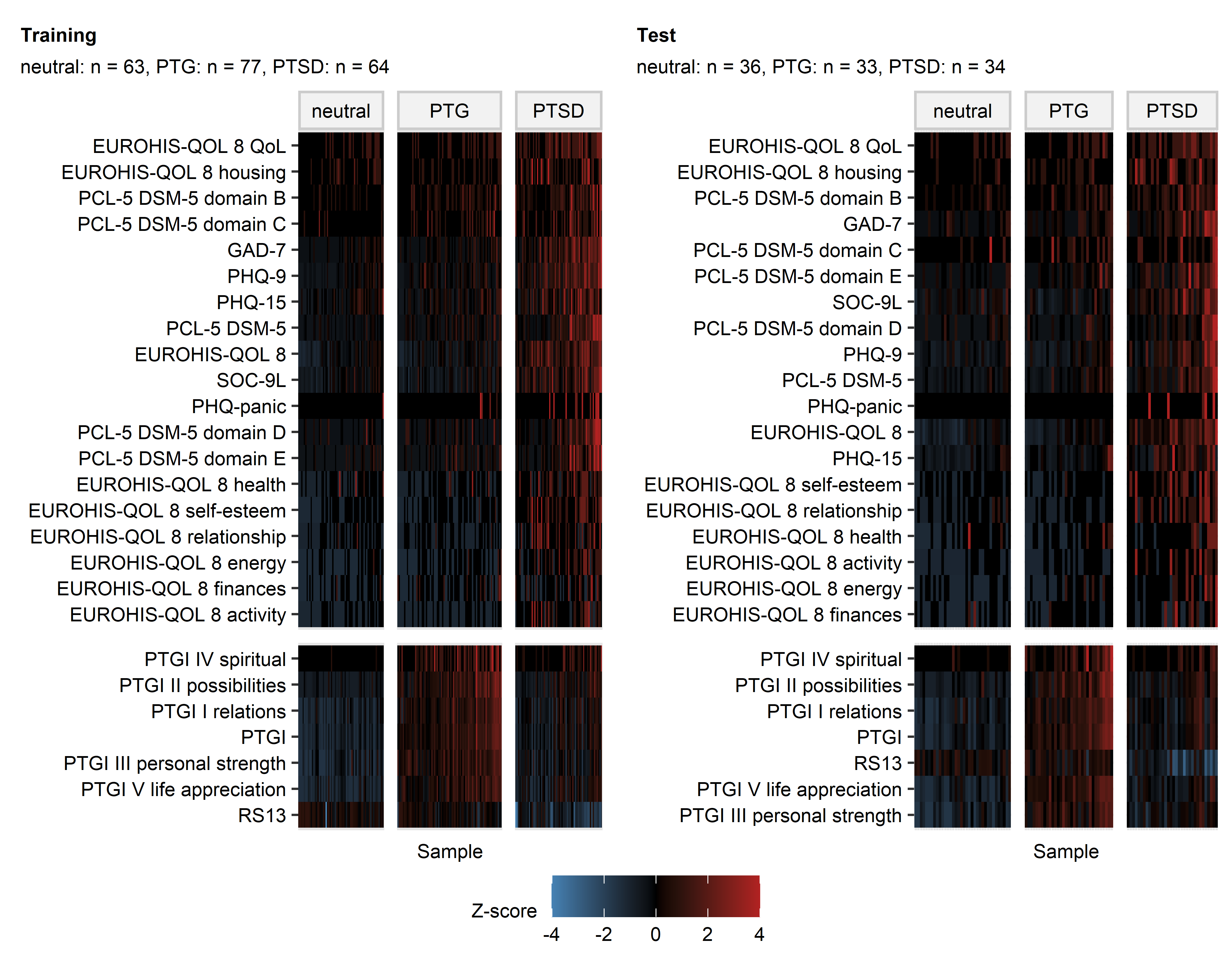


**Supplementary Figure S3. Semi-supervised clustering.**

*The mental clusters were defined in respect to psychometric scoring in the training subset of the study cohort by PAM (partition around medoids) with cosine distance between the observations. Assignment of the test subset observations to the mental clusters was done with the inverse distance weighted 7-nearest neighbors classifier. By this procedure, three mental clusters were identified: neutral, PTG (post-traumatic growth) and PTSD (post-traumatic syndrome disorder). Numbers of observations in the mental clusters are shown in the plot legend in (A).*

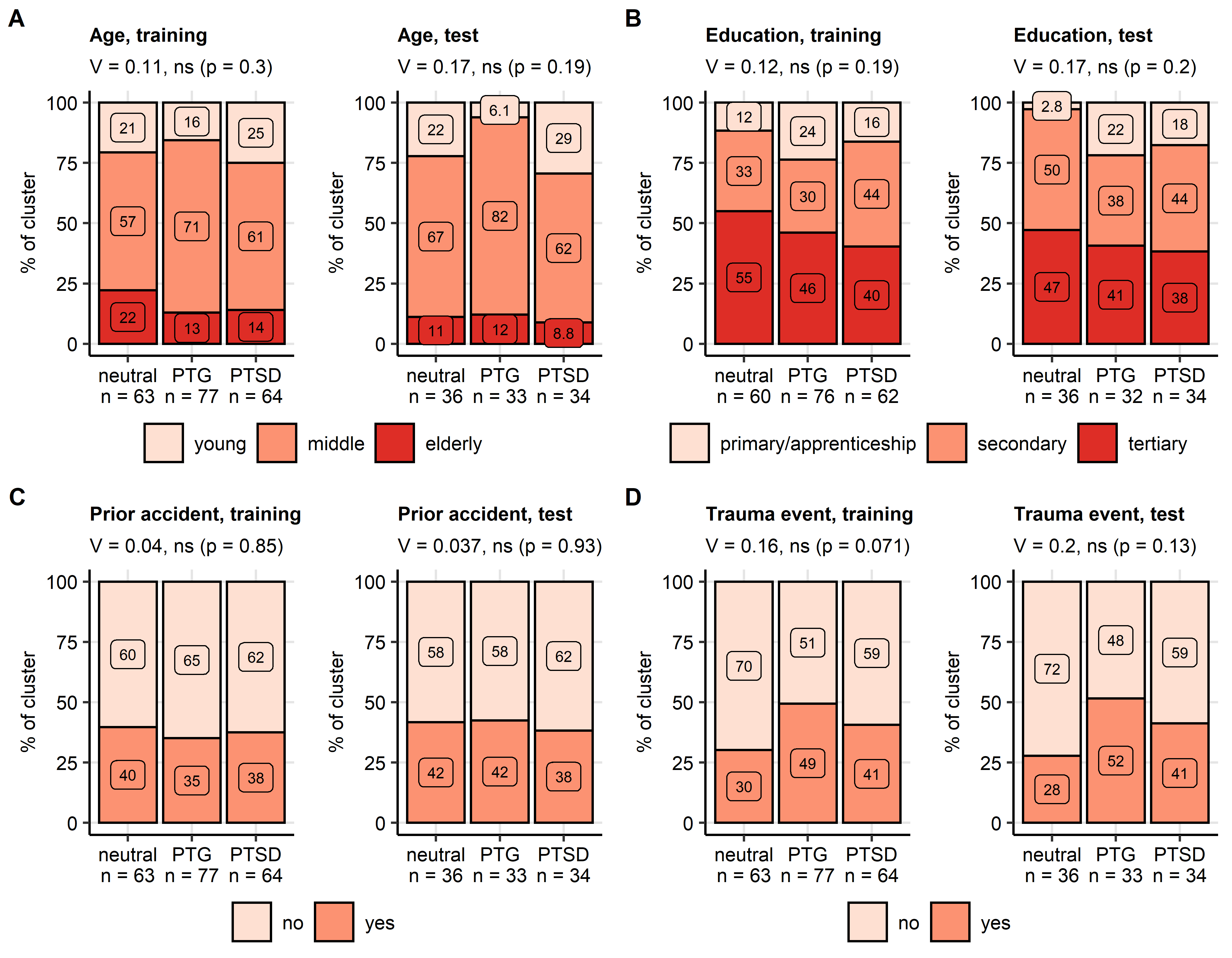
*(A) Observations in the training and test subsets of the study cohorts were subjected to two-dimensional UMAP (uniform manifold approximation and projection) in respect to the psychometric scores. UMAP layouts are shown in scatter plots. Points represent single samples. Point color codes for the cluster assignment.*

*(B) Pairwise cosine distances between observations in the mental clusters of the training and test subsets presented in heat maps.*



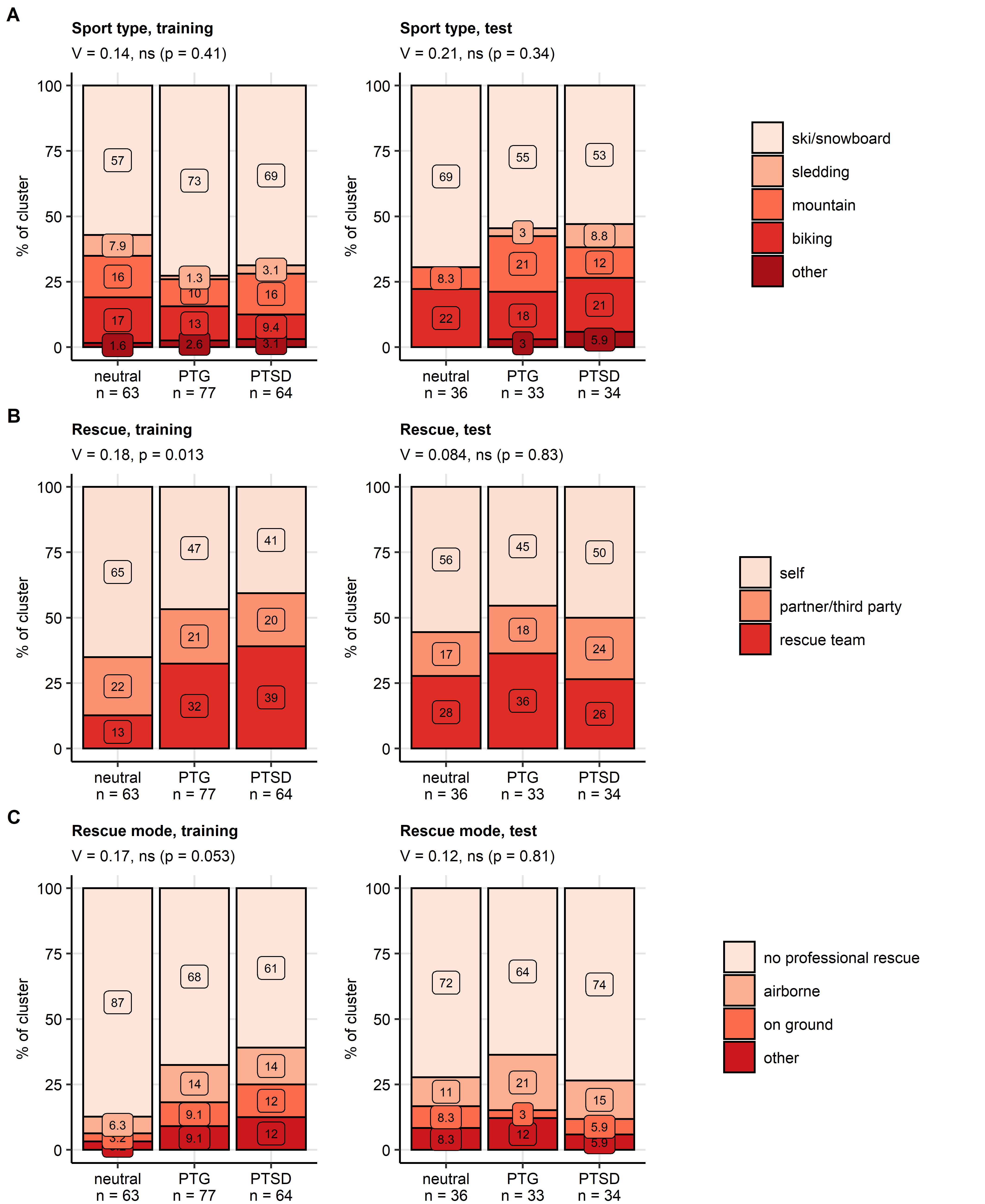
**Supplementary Figure S4. Levels of psychometric clustering scores in the mental clusters.**

*Levels of psychometric scores used in clustering in the mental clusters. Normalized, median-centered score values (Z scores) are presented as heat maps. Numbers of observations in the clusters are displayed in the plot captions. PSS4: 4-item perceived stress scale; GAD-7: 7-item general anxiety disorder scale; PHQ: patient health questionnaire; EUROHIS-QOL 8: 8-item EUROHIS project quality of life scale; SOC-9L: Leipzig 9-item sense of coherence questionnaire; RS13: 13-item resilience scale; PCL-5 DSM-5: PTSD checklist for DSM-5; PTGI: post-traumatic growth inventory; PTSD: post-traumatic syndrome disorder.*



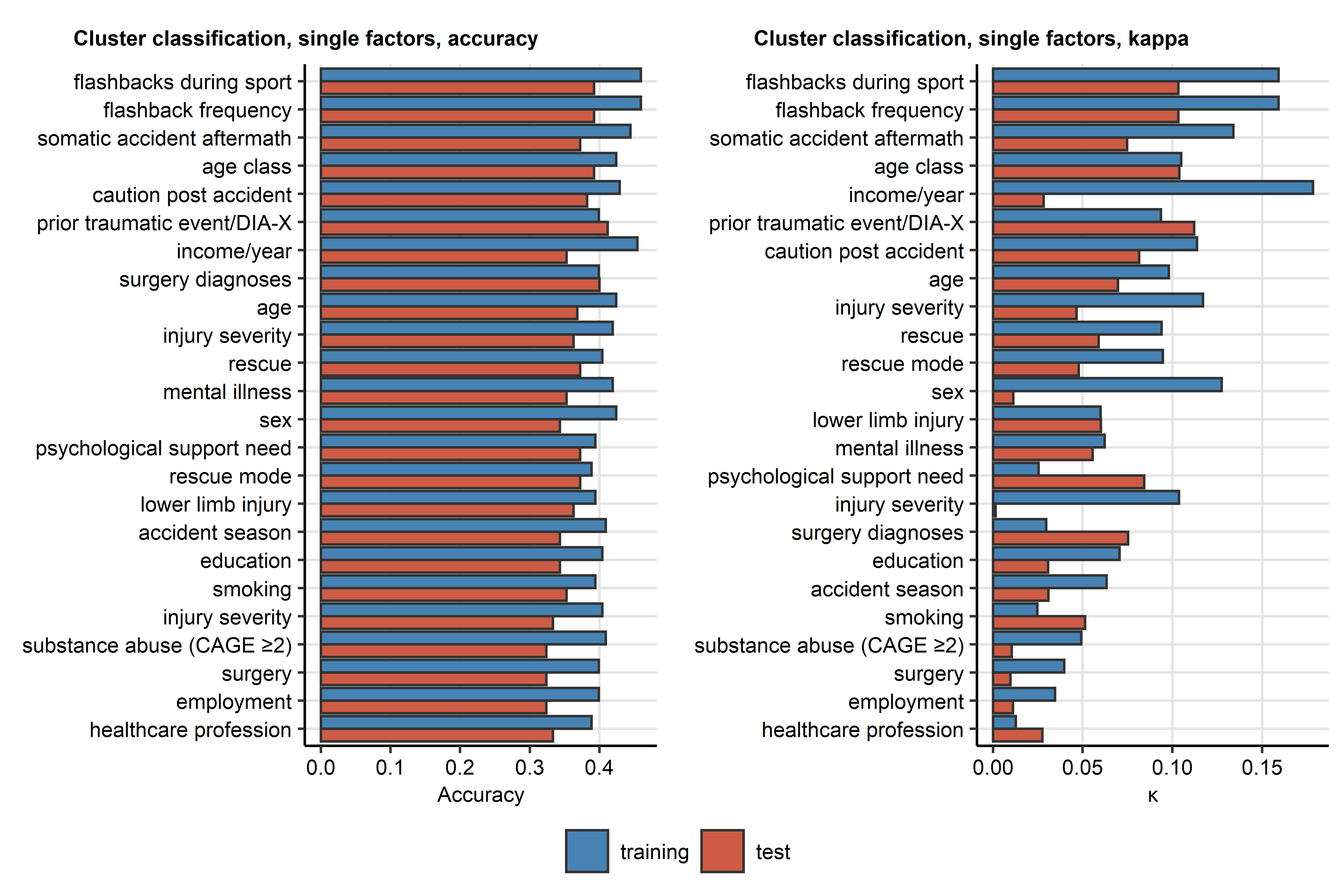
**Supplementary Figure S5. Age, education, household income, prior accidents and traumatic events in the mental clusters.**

*Distribution of age classes (A, young: < 30, middle: 30 - 65, elderly > 65 years), education grades (B), frequencies of prior sport accidents (D) and prior traumatic events (E, measured by the DIA-X tool) in the mental clusters. Statistical significance was determined by test with Cramer V effect size statistic. Percentages in the mental clusters in the training and test subset of the study cohort are presented in stack plots. Effect sizes and p-values are displayed in the plot captions. Numbers of observations in the clusters are presented in the X axes.*



**Supplementary Figure S6. Accident sport type and accident rescue in the mental clusters.**

*Distribution of sport types (A) and rescue modes (B, C) in the mental clusters. Statistical significance was determined by test with Cramer V effect size statistic. Percentages in the mental clusters in the training and test subset of the study cohort are presented in stack plots. Effect sizes and p-values are displayed in the plot captions. Numbers of observations in the clusters are presented in the X axes.*



**Supplementary Figure S7. Prediction of the mental cluster assignment by single demographic, socioeconomic, clinical and accident-related factors.**

*Univariable classifiers of the mental cluster assignment for demographic, socioeconomic, clinical and accident-related parameters were trained in the training subset of the study cohort by the one-rule (oneR) algorithm. The cluster assignment was subsequently predicted for the test subset observations. Accuracy and of the classifiers with any predictive value ( > 0 in both subsets) are shown in bar plots.*

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