



IMMERSE

Implementing Mobile MEntal health Recording Strategy for Europe

H2020 - 945263

D [4.1]	Set of basic statistics for direct implementation and visualization
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Type²	R
Work package	WP4
Work package lead	Georgia Koppe

¹Please choose the appropriate reference:

PU = Public, fully open, e.g. web;

CO = Confidential, restricted under conditions set out in Model Grant Agreement;

CI = Classified, information as referred to in Commission Decision 2001/844/EC.

² Use one of the following codes:

R: Document, report (excluding the periodic and final reports)

DEM: Demonstrator, pilot, prototype, plan designs

DEC: Websites, patents filing, press & media actions, videos, etc.

OTHER: Software, technical diagram, etc

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D [4.1]



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Document history

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(1)	10.12.2021
(2)	08.02.2023

List of abbreviations

ARMA:	auto-regressive moving average
DMMH:	digital mobile mental health
NA:	negative affect
PA:	positive affect
TBD:	to be determined
WP:	work package

Deliverable report

Summary

Deliverable 4.1 of WP4 focused on identifying and implementing simple robust low level statistics and visualizations for the data collected via the DMMH app within the consortium in interaction with WP7 based on prior knowledge within the consortium and existing empirical data. The tasks of WP4 D4.1 thus consisted of agreeing on a set of robust statistics and visualizations, pre-implementing these in Python, and transferring this information to movisens GmbH to be implemented within the DMMH app. All statistics and visualizations were implemented in agreement and collaboration with WP7, the movisens GmbH, and members of the usability lab (Prof. Thomas Ganslandt). The selection of these statistics and visualizations was based on providing a clear and unambiguous application in a clinical setting, as well as technical feasibility. After multiple interactions within the consortium, we narrowed down these statistics to include simple measures capturing distributional properties of the assessed variables, as well as interactions between (as described in excerpt 1 section 1 below), while putting increased emphasis on visualization (as described in excerpt 2 section 2 below). More advanced statistical analyses such as e.g., auto-regressive moving average (ARMA) models and models of mutual predictability, were proposed and thoroughly discussed, but were discarded due to previous experiences and concerns regarding interpretation difficulties on the clinical side. Suggestions regarding the pooling of data across subjects to gain deeper clinical insights were also discontinued for now due to data privacy concerns.

Basic versions of agreed upon statistics and visualizations were implemented in Python, as well as tested on pre-existing data provided by members of the consortium. A joint document shared with movisens GmbH was compiled to provide more detailed descriptions and instructions for implementation on these statistics and visualizations, specifying for instance on which variables statistics and visualizations shall be performed, and providing illustrative examples. This document serves to transfer statistics and visualizations identified in WP4 to the movisens GmbH and is taken as foundation for the following report. Excerpts of this joint document are presented as deliverable here.

1. Robust statistics

In the following, we summarize the agreed upon statistics for the DMMH dashboard. The statistics include the computation of means and medians, standard deviations, percentiles, correlation measures, trend lines, and significance tests. The following excerpts of the instruction protocol were purpose-built for the information transfer to movisens GmbH. Please note that this instruction protocol is part of a larger document with multiple other cross-referenced sections and we provide here only the relevant sections for this deliverable.

Excerpt of joint protocol between movisens GmbH and WP4:

All statistics are computed based on the service user's input. Some of them are limited in the applicability to the amount of data that is available.

Computation of average (mean) affect

To keep the affective scores as universal as possible across all subjects, we decided to compute the overall positive affect (PA) score based on the mean score of all positive momentary mood items (that is, 'happy', 'enthusiastic', 'relaxed', 'content'), and compute the overall negative affect (NA) score based on the mean score of all negative momentary mood items (that is, 'anxious', 'irritated', 'sad', 'insecure'). The scores will be computed according to:

$$PA_{mean} = \frac{(happy+enthusiastic+relaxed+content)}{4N}, \text{ and}$$
$$NA_{mean} = \frac{(anxious + irritated + sad + insecure)}{4N}.$$

Depending on the selected timeframe and resolution of the time series visualization plots, the average is either formed per questionnaire (N=1) or per day, where N corresponds to the number of questionnaires filled out per day.

Computation of means, medians, standard deviation, and percentiles

Means and medians may be computed either for the positive affect and negative affect scores, or for individual mood items. Medians are generally more robust to statistical outliers (e. g., accidentally faulty input), so they are to be preferred particularly for individual mood items.

Standard deviations and percentiles which display the width of a distribution should only be computed when sufficient amounts of data are available. In the context of the expected frequency of EMA sampling, time frames of around one week should provide sufficient input data. Hence, displaying either weekly summary distributions (which can then also reflect

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changes in distributions across weeks) or one global summary statistic for all datapoints of the respective patient are most sensible here.

To display the width of a distribution (in bar or line graphs) on top of the mean, the corrected standard deviation of the sample is computed by dividing the sum over the quadratic deviations from the mean by the corrected number N-1:

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2},$$

where N is the number of data points in the sample, x_i is a single data point, and \bar{x} is the sample mean.

In case of multiple outliers, where the median is preferred over the mean, percentiles should be displayed. The median by definition splits the data into a 50% percentile, meaning half of the data is contained above and below. The difference between the 75% quartile and the 25% quartile serves as a robust estimate of variance of the distribution (IQR, Inter Quartile Range). To obtain it, values for the 75% and 25% percentiles are computed (e.g. using `np.percentile` in Python) and subtracted from each other.

Computation of correlation measures

Correlations between mood items are computed based on Kendall's τ and Spearman's ρ which provide robust statistical estimates of the correlation between ordinal variables. They are pre-implemented in popular statistical toolboxes, e.g. `scipy.stats` in Python. A complete correlation matrix can then be computed for all items of the respective patient. The entries of this matrix contain the respective pairwise correlation coefficients.

Correlations between two specific items can then be selected from this matrix by the clinician. Alternatively, a significance test can be computed for all correlation values (e.g. by employing `scipy.stats.spearmanr.pvalue`). In this case, a multiple-comparison correction needs to be taken into account by dividing the respective p-value (e. g., $p=0.05$) by the number of comparisons. For N mood items, this number is given by $N(N-1)/2$. The resulting matrix can be masked with the chosen corrected significance threshold to obtain a matrix that only contains statistically significant correlations.

Computation of trend lines

Trends are computed item-wise between different dedicated time periods that are either fixed (e. g., one week before and after intervention) or selected by the clinician. To obtain a trend, the total average score of an item is computed by the sum over all Likert scale scores of the respective item in the selected time period, divided by the total number of points. Both averages are then subtracted from each other to obtain the trend in the given time period. Depending on whether it is a trend per time period/day/beep, the trend needs to be normalized with the total number of questionnaires filled out in the respective time intervals.

Computation of mean differences between context items

To assess whether shifts in positive and negative affect means across different context items and timeframes are statistically significant in the bar chart (see visualization 2.4), (e.g., to infer

whether positive affect while at work vs. positive affect when home alone differs significantly), an analysis of variance (ANOVA) test is computed. The input is a list of all positive/negative affect items across a given time interval for each context items that is compared, respectively. When, for instance, using `scipy.stats.f_oneway` in Python, a p-value above 0.05 indicates no significant change in mean between population means, while a p-value below 0.05 indicates a significant change. If all pairwise distributions are compared (e.g., positive affect while at work vs. positive affect when alone and positive affect while at work vs. positive affect while with friends etc.), then again a multiple test comparison needs to be applied by dividing the respective p-value by $N(N-1)/2$, where N is the number of are all context items. Similar to the correlation matrix, all cases of significant differences may then be computed and given as feedback.

2. Visualizations

In the following, we summarize the agreed upon visualizations for the DMMH dashboard. The visualizations include time graphs, pie charts, box plots, bar charts, text output, correlation matrix, trend lines, and hexagons.

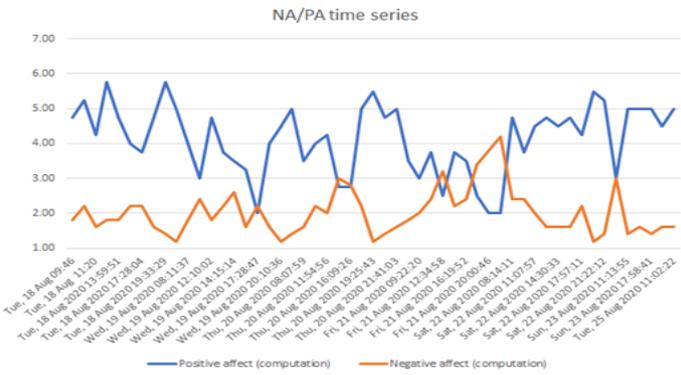
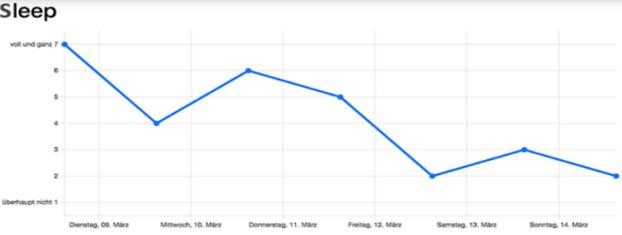
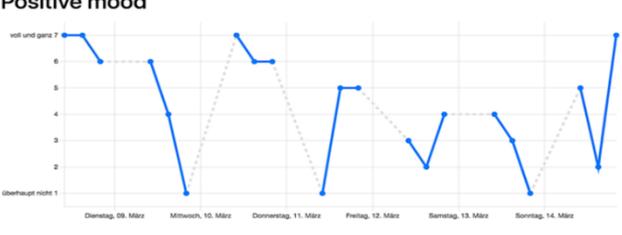
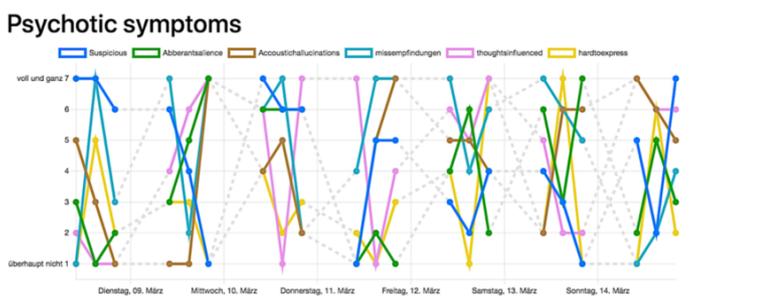
Excerpt of joint protocol between movisens GmbH and WP4:

Visualizations are displayed through the MoMent dashboard according to data visualization output styles defined below. Visualizations were pre-implemented by WP4 in Python and provided to movisens as examples.

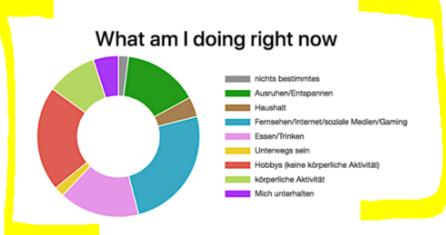
2.1 Timeline graph, shows peaks and valleys, representing the variation of, e.g., positive and negative affect experienced during a selected timeframe. By zooming in a specific time point, the clinician gains extra insight into the experience of the service user in that specific moment.

Name	Timeline graph
Description	<p>Graph that allows clinicians to see the evolution in, e.g., specific mood items, sleep, or over-all positive and negative affect over a specific time period.</p> <p>Some ESM items are prompted several times per day and others are asked once per day (e.g., morning). Thus, some line graphs would need one data point per day and others several.</p> <p>Clinicians should be able to toggle which mood and affect graphs to see, via a selection menu next to the graph. Constructs are often assessed with several ESM items. In this graph the clinician can also toggle different items (i.e. take out colored lines) within the graph, which makes it possible to see basic relationships between items on a first glance. Clinicians should be able to select the time period (e.g., 7 days, 14 days), for which they want to see data via a selection menu next to the graph. Clinicians should be able to examine specific time points in detail (receiving information about context at that moment), by clicking or hovering over a time point. Missing data should be shown as missing on the graph.</p>
Type of visualization	Line graph



<p>Data</p>	<p>Data items can be visualized with this type of graph include:</p> <ul style="list-style-type: none"> • Positive affect • Negative affect • Average positive and negative affect • Sleep quality • Key problems (main complaints)
	<div style="text-align: center;">  <p>NA/PA time series</p> </div> <div style="margin-top: 20px;"> <p>DISERVE @ Home Sign out</p> <p>Subject 1 June 10, 2021 - June 17, 2021</p> <p>Therapy Goals (Weekly) Therapy goals (daily: evening) sleep</p> <p>Positive mood Main complaints Psychotic symptoms activities Active Social everyday life Medication substance Moments of joy Activity planner</p> <div style="display: flex; flex-direction: column; align-items: center;"> <div style="margin-bottom: 10px;"> <p>Sleep</p>  </div> <div style="margin-bottom: 10px;"> <p>Positive mood</p>  </div> <div> <p>Psychotic symptoms</p>  </div> </div> </div>

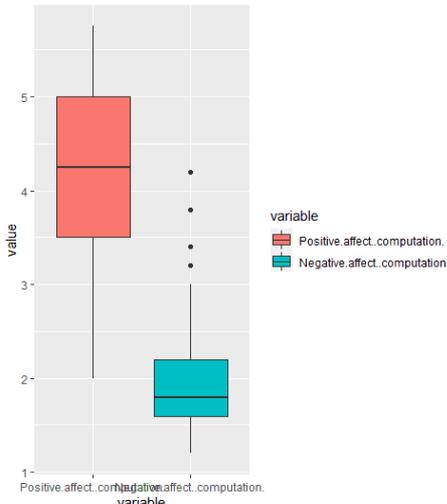
2.2 Pie chart / donut, illustrating, for example, the amount of time the service user spends in company or alone and the amount of time he/she has been involved in specific activities during a selected timeframe. This provides information on the social and contextual aspect of the service user experience, indicating the percentage he/she is involved in specific activities or social interactions.

Name	Context overview																											
Description	Graphs that provide an overview of the different activities, social and situational contexts reported by the client. Time as an overall, relative percentage																											
Type of visualization	Pie chart																											
Data	Context (location, main activity, social interaction)																											
Example	 <p>DISERVE @ Home</p> <p>Subject 1 June 10, 2021 - June 17, 2021</p> <p>Therapy Goals (Weekly) Therapy goals (daily: evening) sleep Positive mood Main complaints Psychotic symptoms</p> <p>activities What am I doing right now</p> <p>Active Social everyday life Medication substance Moments of joy Activity planner</p> <p>Activities</p> <p>What am I doing right now</p>  <table border="1"> <thead> <tr> <th>date</th> <th>Time</th> <th>activities</th> <th>answer</th> </tr> </thead> <tbody> <tr> <td rowspan="6">Thursday, March 12th, 2021</td> <td rowspan="3">13:00</td> <td>I am doing this right now:</td> <td>Eat Drink</td> </tr> <tr> <td>What I'm doing right now is enjoyable.</td> <td>Fully</td> </tr> <tr> <td>What I'm doing is easy for me.</td> <td>Fully</td> </tr> <tr> <td rowspan="3">18:00</td> <td>I am happy with this activity</td> <td>Not at all</td> </tr> <tr> <td>I am doing this right now:</td> <td>Physical activity</td> </tr> <tr> <td>What I'm doing right now is enjoyable.</td> <td>Not at all</td> </tr> <tr> <td></td> <td></td> <td>What I'm doing is easy for me.</td> <td>Not at all</td> </tr> <tr> <td></td> <td></td> <td>I am happy with this activity</td> <td>Not at all</td> </tr> </tbody> </table>	date	Time	activities	answer	Thursday, March 12th, 2021	13:00	I am doing this right now:	Eat Drink	What I'm doing right now is enjoyable.	Fully	What I'm doing is easy for me.	Fully	18:00	I am happy with this activity	Not at all	I am doing this right now:	Physical activity	What I'm doing right now is enjoyable.	Not at all			What I'm doing is easy for me.	Not at all			I am happy with this activity	Not at all
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		What I'm doing is easy for me.	Not at all																									
		I am happy with this activity	Not at all																									

2.3 Boxplots, providing an overview of the intensity of, e.g., positive and negative affect experienced during a selected timeframe. This visualization mode displays an average for a specific time period and indicates whether the service user's mood was stable or whether it fluctuates during this time. Short boxes and whiskers in this graph suggest that the service user's mood is stable over time whereas longer boxes and whiskers suggest some variability, thus e.g. great fluctuation of positive and negative emotions during the week.

Name	Summary boxplots
Description	Graphs that summarize mood and affect showing mean value as well as inter-quartile range, max, min and outliers.
Type of visualization	Box plots

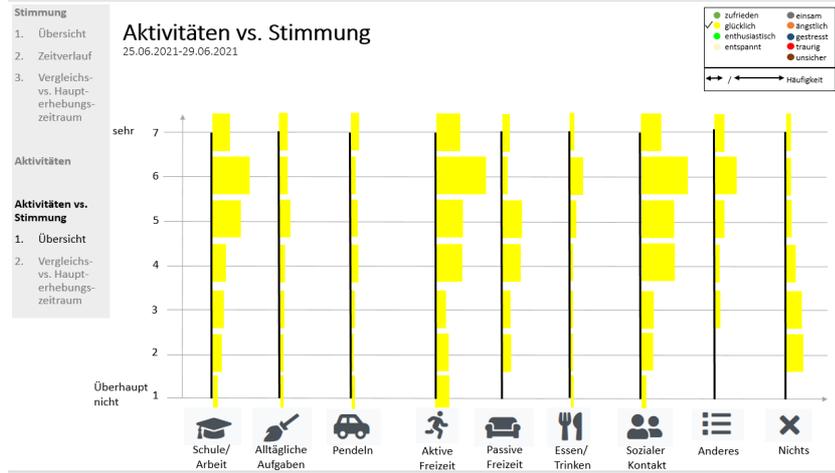


Data	TBD.
Example	 <p>Example of PA/NA intensity summaries.</p>

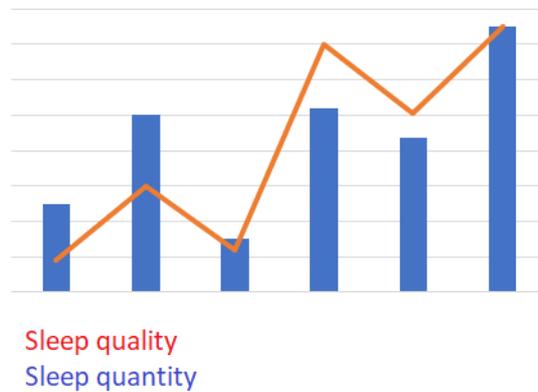
2.4 Bar chart, providing an overview of the service user’s mood in relation to a specific context, activity, or social interaction. This visualization mode allows the clinician to investigate a service user’s mood within a specific context, in relation to a specific activity or social experience. Whereas assessing mood variation, daily activity, and social context separately can provide useful information to clinicians, combining these three aspects allows a comprehensive understanding of how service users react to a specific context or social situation. This information could be extremely useful to detect possible triggers in the context and also shed light, during the intervention, on the underpinning changing mechanisms.

Name	Distributions in combination with X
Description	Graphs that shows how mood and affect varies in relation to context
Type of visualization	Bar chart (horizontal and vertical)
Data	Mood items - core module + Context items - core module (location, main activity, social interaction) Sleep quantity

Examples



Sleep overview



2.5 Text output

Name	Text output
Description	In the form of a scrollable table, any output from e.g. open text items can be read with date and timestamp This could be used in combination with doughnut charts to offer more detailed (temporal) information on the constructs.
Type of visualization	Table
Data	TBD. string text



Example

2.6 Correlation Matrix

Name	Correlation matrix
Description	A table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables. A correlation matrix is used to summarize data, as an input into a more advanced analysis, and as a diagnostic for advanced analyses.
Type of visualization	Table
Data	TBD: Add-on modules
Example	

2.7 Simple trend line

Name	Trend line
Description	An added line summarizing the general direction of the data.
Type of visualization	Line graph
Data	TBD: Any line graph.



2.8 Hexagon

Name	Hexaflex
Description	An overview of construct tendencies
Type of visualization	Hexagon
Data	TBD: Add-on modules
Example	<p>Hier en Nu</p> <p>Acceptatie</p> <p>Waarden</p> <p>Toegewijde Actie</p> <p>Zelf als Context</p> <p>Defusie</p>

