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Supplementary Material

Article Title: Prospective Memory Influences Social Functioning in People With First-Episode Schizophrenia: A Network Analysis and Longitudinal Study

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List of Supplementary Material for the article

Disclaimer

Supplementary Materials

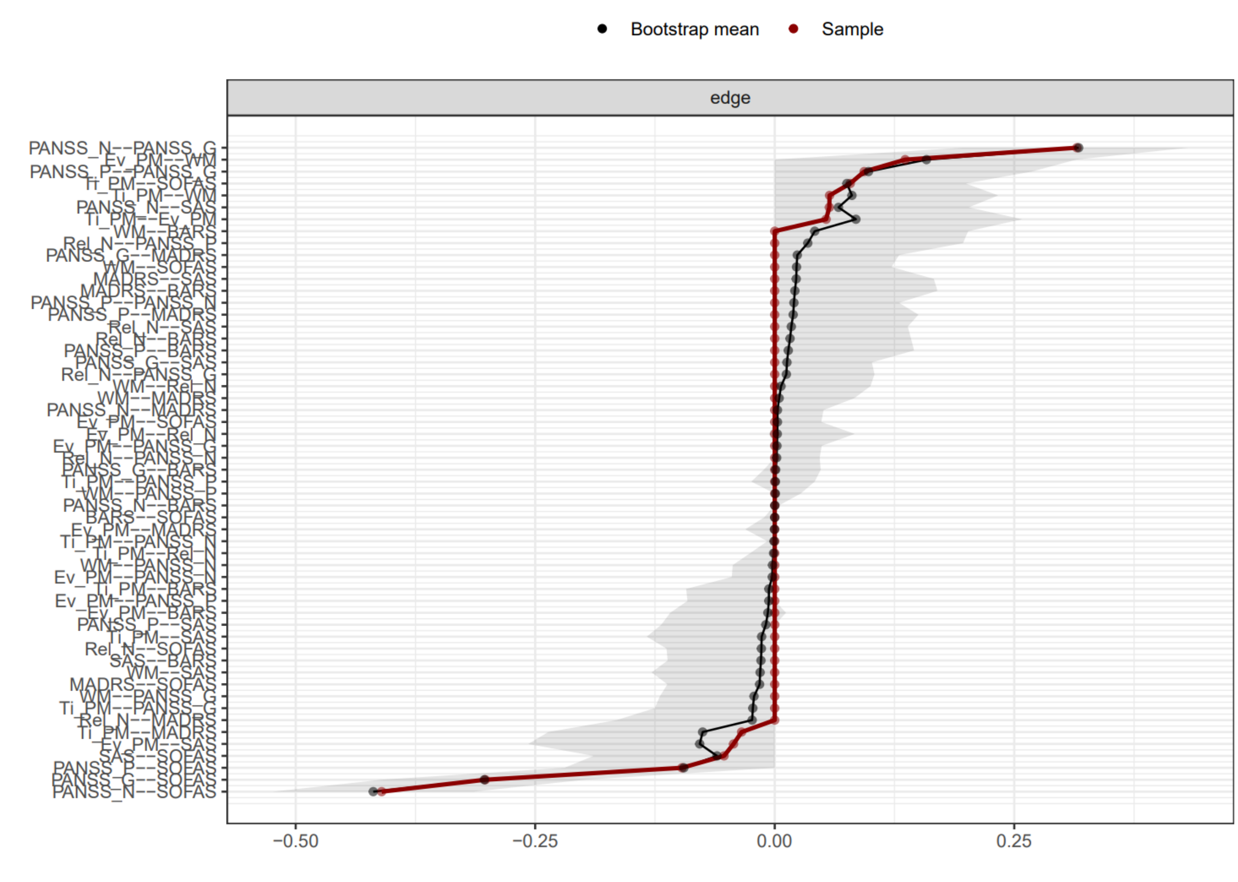
Supplementary Table 1. Previous studies investigating the relationship between prospective memory (PM) and functional outcomes in schizophrenia patients

Study	Sample	Study design	PM measure	Functional outcome Measures	Other outcome measures	Clinical symptoms	Other cognitive measures	Summary of results	Limitations
Twamley et al. (2008) [8]	72 SCZ patients	• Single group • Cross-sectional • Regression analysis	The Memory for Intentions Screening Test (MIST)	UCSD Performance-Based Skills Assessment-Brief Version	None	PANSS, HAM-D	IQ, LNT, visual memory, WCST, digit span, Trail making, continuous performance test	Better PM was predictive of higher functional capacity	(1) Only 58 of 72 SCZ patients had completed social functioning measurement (2) Small sample size (3) Medication adherence was not measured (4) Cross-sectional design cannot infer causal relationships
Au et al. (2014) [6]	44 SCZ patients	• Single group • Cross-sectional • Correlational analysis • Regression analysis	The Cambridge Prospective Memory Test (CAMPROMPT)	The Functional Needs Assessment (FNA)	None	PANSS	RM, IQ	PM was correlated with community living skills but not self-care. PM predicted community living skills after controlling for IQ and delayed recall	(1) Small sample size (2) Medication adherence was not measured (3) Cross-sectional design cannot infer causal relationships
Raskin et al. (2014) [10]	41 SCZ patients, 25 controls	• Case-control • Cross-sectional • Comparative statistics • Correlational analysis • Regression analysis	The MIST	None	Medication adherence, as measured by the MMAA	PANSS	Trail making test, verbal learning	SCZ patients had poorer PM than controls, PM predicted medication management ability after controlling for verbal learning	(1) Small sample size (2) cross-sectional design cannot infer causal relationships (3) Lack of social functioning measures

								and executive functions	
Xiang et al. (2010) [44]	110 SCZ patients	• Single group • Cross-sectional • Correlational analysis • Regression analysis	A computerized PM paradigm	FNA	None	BPRS	IQ, Design Fluency Test, Tower of London, WCST, RM	PM was not correlated with social functioning	(1) PM was not the key cognitive variables to be measured (2) Limited measures of SF
Burton et al. (2019) [7]	58 SCZ, 37 BD, 58 MDD	• Case-control • Cross-sectional • Correlational analysis • Regression analysis	The MIST	(1) UCSD Performance-Based Skills Assessment-Brief Version. (2) work outcomes	None	None	None	PM predicted functional capacity and work duration in the entire sample	(1) Subjects with different diagnosis were recruited (2) Did not measure other cognitive functions (3) Did not measure clinical symptoms

Note: BD = Bipolar disorder, BPRS = Brief Psychiatric Rating Scale, IQ = intelligence, MDD = major depression, MMAA = Medication Management Ability Assessment, PANSS = Positive and Negative Syndrome Scale, PM = prospective memory, RM = retrospective memory, SCZ = schizophrenia, SF = social functioning, WCST = Wisconsin Card Sorting Test.

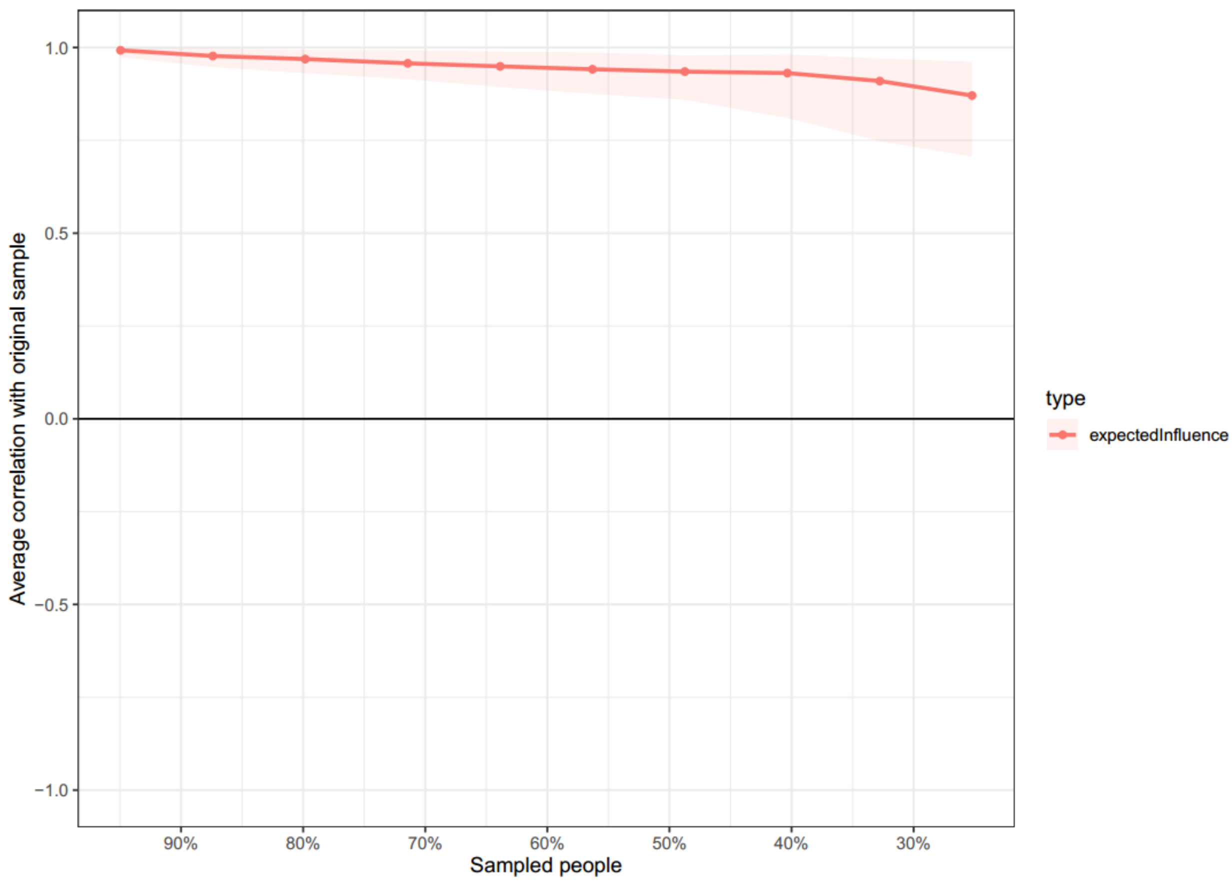
Supplementary Figure 1.



Supplementary Figure 1. The sample mean and bootstrapped mean of the edge weights (R) with the 95% CI in the network depicted in Figure 1.

The black dots indicate the sample mean, whereas the red black dots indicate the bootstrapping mean, for each of the edge weight. The shadowed area shows the range of R falling within the 95% CI. Edge having a R with 95% CI above and below zero indicates better stability.

Supplementary Figure 2.



Supplementary Figure 2. Stability of the network

The y-axis represents the correlation between the EI of all the nodes in the original network and the EI of all the nodes in the network constructed using bootstrapping method of a proportion of the original sample. The x-axis represents the percentage of sampled population in descending order. The red dots indicate the correlation coefficients between the EIs of the two networks. Shadowed areas represent 95% CI of the correlation coefficients.

The Syntax for Network Analysis

```
########library basic toolbox######


library("qgraph")

library("gdata")

library("readxl")

library('mgm')


library(mnormt)

library(nortest)


Data_HK_T1 <-
as.data.frame(read_excel("C:\\networkTry\\HK\\Cognition_Symptoms_SF_cog_symp_SF_T1.xls
x",sheet=1,na = "."))

head(Data_HK_T1)


library(mvnormtest)

mshapiro.test(t(Data_HK_T1[1:11]))


#########normalization############

library(huge)

Data_HK_T1_trans <- huge.npn(Data_HK_T1, npn.func = "shrinkage", verbose = TRUE)

mshapiro.test(t(Data_HK_T1_trans[1:11]))


Names <- scan("C:\\networkTry\\HK\\Nodename2.txt",what = "character", sep = "\n")


Groups1 <- c(rep("PM",2),rep("WM",1),rep("Number of relapse",1),rep("PANSS",3),
rep("MADRS",1),rep("SAS",1),rep("Barthes",1),rep("Social functioning",1))
```

```
#######Predictivity calculation########

set.seed(1)

fit_obj <- mgm(data = Data_HK_T1_trans, type = rep('g', 11), level = rep(1, 11), lambdaSel =
'CV',

            ruleReg = 'OR')

pred_obj <- predict(object = fit_obj,

                data = Data_HK_T1_trans,

                errorCon = 'R2')

pred_obj$error #####show value


smallNetwork <- estimateNetwork(Data_HK_T1_trans, default="EBICglasso", tuning=0.25)

graph_small <- plot(smallNetwork, layout = "spring", pie=pred_obj$error[,2], cut=0, vsize=7,

                filename="HK_Network_Final_Trans", width=6, height=5, repulsion=1.1,

                border.color='#555555', label.color="#555555", labels = colnames(Data_HK_T1),
nodeNames=Names, groups=Groups1, legend.cex = 0.35, filetype="pdf", theme='colorblind')

smallNetwork$graph


####expected influence########

smallNetwork$graph

EI_s <- scale(colSums(smallNetwork$graph))

EI_s


plot(EI_s, ylab="Expected Influence", xlim=c(1,11), ylim=c(-3,3),xaxt='n')

abline(h=0,col="black", lty = 3)

abline(h=c(-3,-2,-1,1,2,3), col="#d6d6d6")
```

```
axis(1, at=c(1,2,3,4,5,6,7,8,9,10,11),labels=c("Ti_PM","Ev_PM","WM","Rel_N",
"PANSS_P","PANSS_N","PANSS_G","MADRS","SAS","BARS","SOFAS") )

lines(EI_s, type="l", col="#555555")


################stability analysis###########################


################node stability################################

boot1<-bootnet(smallNetwork, nBoots=1000, type="case",nCores=1)

plot(boot1,labels = FALSE) #edge-weight stability

corStability(boot1)

### Centrality stability coefficient (value)

corStability (boot1, statistic="expectedInfluence")##0.75



################edge stability################################

boot2 <- bootnet(smallNetwork, nBoots = 1000, nCores = 1)

plot(boot2, order = "sample")



######Normality checking for single variable############

shapiro.test(t(Data_HK_T1[1]))

shapiro.test(t(Data_HK_T1[2]))

shapiro.test(t(Data_HK_T1[3]))

shapiro.test(t(Data_HK_T1[4]))

shapiro.test(t(Data_HK_T1[5]))

shapiro.test(t(Data_HK_T1[6]))

shapiro.test(t(Data_HK_T1[7]))
```

```
shapiro.test(t(Data_HK_T1[8]))
shapiro.test(t(Data_HK_T1[9]))
shapiro.test(t(Data_HK_T1[10]))
shapiro.test(t(Data_HK_T1[11]))
```