

# **Topic:**

Examine the Effectiveness of Psychological Treatments in Alleviating Depressive Symptoms for Diabetes

# **Modeling method:**

Random Slope and Intercept Model

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#### **Introduction:**

According to the National Diabetes Statistics Report, 38.4 million people have diabetes (11.6% of the US population). [1]. Diabetes is a chronic disease that affects the transformation of food into energy, breaking down most of the food in the body into sugar (glucose) and releasing it into the bloodstream. According to the Life Line Screening [2], the main difference between the two types of diabetes is:

- Type I diabetes is a genetic disorder that often shows up early in life.
- Type II is largely diet-related and develops over time.

Diabetes not only impacts the physical well-being of patients but also takes a toll on their mental health. A significant portion of individuals grappling with diabetes experience symptoms of depression. Depression and diabetes are common coexisting conditions that have a debilitating impact on each other [3].

Types of Psychological Treatments for Diabetes:

• Cognitive Behavioral Therapy (CBT):

Focuses on identifying and challenging negative thought patterns directly, aiming to change them into more positive and adaptive ones through structured exercises and homework assignments.

• Mindfulness-Based Cognitive Therapy (MBCT):

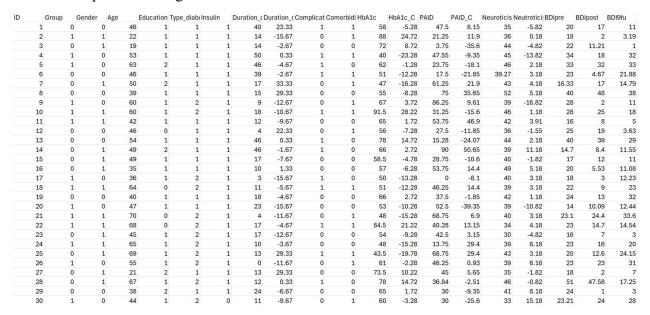
Integrates mindfulness practices with cognitive therapy techniques. It encourages individuals to observe their thoughts and emotions without judgment, and acceptance to prevent relapse and manage symptoms.

# **Data Description:**

The dataset is sourced from the "What Works Best for Whom" study[4], studying which is more effective in reducing depression levels among diabetes patients: CBT or MBCT.

In this longitudinal dataset patients were followed for a year, and BDI score (severity of depressive symptoms) were measured at pre-treatment, post-treatment, and at the 9-month follow-up. The response variable is the BDI score where the predictors include Group of treatment, Gender, Age, Education level, Type of diabetes, Comorbidities, and Neuroticism.

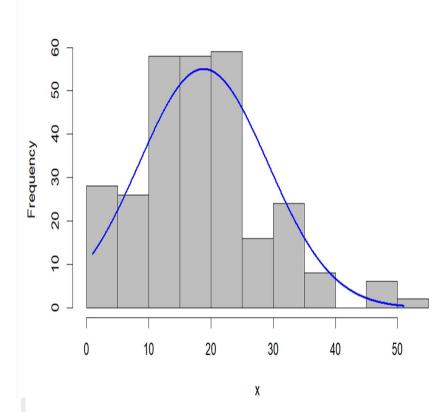
# Before manipulation using R



# After manipulation using R

ID	Age	Neuroticis	Month	<b>BDIscore</b>	Group	Gender	Education Type_diab	Comorbidities
	1 46	35	0	20	MBCT	Male	Intermedia Type I	Yes
	2 22	36	0	18	CBT	Female	Intermedia Type I	Yes
	3 19	44	0	22	MBCT	Female	Intermedia Type I	No
	4 53	45	0	34	CBT	Male	Intermedia Type I	Yes
	5 63	46	0	33	CBT	Male	High Educa Type I	No
	6 46	39.27	0	23	MBCT	Male	Intermedia Type I	Yes
	7 50	43	0	16.33	MBCT	Female	High Educa Type I	Yes
	8 39	52	0	40	MBCT	Male	Intermedia Type I	No
	9 60	39	0	28	CBT	Male	Intermedia Type II	Yes
	10 60	46	0	28	CBT	Female	Intermedia Type II	Yes
	11 42	42	0	16	CBT	Female	Intermedia Type I	No
	12 46	36	0	25	MBCT	Male	Low Educa Type I	Yes
	13 54	1 44	0	40	MBCT	Male	Intermedia Type I	No
	14 49	39	0	14.7	MBCT	Female	High Educa Type I	No
	15 49	40	0	17	MBCT	Female	Intermedia Type I	No
	16 35	49	0	20	MBCT	Female	Intermedia Type I	No
	17 36	40	0	18	CBT	Male	Intermedia Type II	No
	18 64	1 39	0	22	CBT	Female	Low Educa Type II	Yes
	19 40	42	0	24	MBCT	Male	Intermedia Type I	No
	20 47	7 39	0	14	CBT	Male	Intermedia Type I	No
	21 70	40	0	23.1	CBT	Female	Low Educa Type II	Yes
	22 68	34	0	23	CBT	Female	Low Educa Type II	Yes
	23 45	30	0	16	MBCT	Female	Intermedia Type II	No
	24 65	39	0	23	CBT	Female	Intermedia Type II	No
	25 69	43	0	20	MBCT	Female	Intermedia Type II	Yes

# **Results:**



Shapiro-Wilk normality test

data: longform.Diabetic\$BDIscore
W = 0.96803, p-value = 5.771e-06

The histogram is right-skewed, so the data of the response variable BDI score is not actually normally distributed.

	Value <chr></chr>	Std.Error <chr></chr>	<b>DF</b> <chr></chr>	t-value <chr></chr>	p-value <chr></chr>
(Intercept)	-21.578252	6.193880	189	-3.483802	0.0006
Group.relCBT	0.807103	1.491888	86	0.540994	0.5899
Gender.relMale	4.702615	1.327690	86	3.541953	0.0006
Age	0.294769	0.066455	86	4.435610	0.0000
Education.relLow Education	4.115252	2.901731	86	1.418206	0.1597
Education.relIntermediate Education	3.097370	2.386974	86	1.297613	0.1979
Type_diabetes.relType I	2.875266	1.886792	86	1.523891	0.1312
Comorbidities.relYes	-2.089979	1.553127	86	-1.345659	0.1819
Neuroticism	0.534734	0.126251	86	4.235492	0.0001
Month	-0.406505	0.088036	189	-4.617508	0.0000

$$\hat{E}(BDI\,score) = -21.578252 + .807103\,CBT + 4.702615\,Male + .294769\,Age + \\ 4.115252\,Low\,Education + 3.097370\,Intermediate\,Education + 2.875266\,Diabetes\,Type\,I \\ -2.089979Comorbidities + .534734\,Neuroticism - .406505\,Month.$$

$$\hat{\sigma}_{u_1}^2=60.6100$$
 ,  $\,\hat{\sigma}_{u_2}^2=0$  ,  $\hat{\sigma}_{u_1u_2}=1.4350$  ,  $\hat{\sigma}^2=1.4246$ 

Male, age, neuroticism, and month are the significant predictors at level of 5% among all the variables.

For males, the estimated average BDI score (severity of depressive symptoms) is 4.702615 points higher than that for females.

As age increases by one year, the estimated average BDI score increases by 0.294769 points.

As the neuroticism level increases by one unit, the estimated average BDI score increases by 0.534734 points.

As time in the study increases by one month, the estimated average BDI score decreases by 0.406505 points.

# **Conclusion:**

Based on the results we obtained, we can conclude that psychological treatments have a significant impact on alleviating depressive symptoms in diabetic patients over time. However, we can also conclude that there is no significant difference between the CBT treatment and MBCT treatment for diabetic patients, as the p-value of the CBT treatment is greater than 5%. The "What Works Best for Whom" study found that both therapies, CBT and MBCT, helped reduce depression in diabetic patients, which supports the results we obtained.

#### Code:

#### R

```
Diabetic ← read.csv(file = "C:/Users/bushr/OneDrive/Desktop/CBT_MBCT.csv", header=TRUE, sep=",")
#1.Data transformation: categorization
Diabetic ←
Diabetic %>%
  mutate(
     Group = factor(Group, levels=c(1,0), labels=c("CBT", "MBCT")),
Gender = factor(Gender, levels = c(1,0), labels= c("Female", "Male")),
Education = factor(Education, levels = c(0,1,2), labels=c("Low Education"
                                                                                 "Intermediate Education", "High Education")),
     Type_diabetes = factor(Type_diabetes, levels=c(2,1), labels=c("Type II", "Type I")), Comorbidities = factor(Comorbidities, levels=c(1,0), labels=c("Yes", "No"))
#2.Create long - form data set
#2.1 Rename and transform to numeric
longform.Diabetic \leftarrow longform.Diabetic %>%
  rename(Month = variable, BDIscore = value) %>%
    mutate(Month = recode(Month, "BDIpre" = 0, "BDIpost" = 3, "BDI9fu" = 12))
#3 Testing the normality of the value
##3.1 Histogram Plot
plotNormalHistogram(longform.Diabetic$BDIscore)
##3.2 Shapiro Test
shapiro.test(longform.Diabetic$BDIscore)
#4.Specifying reference category
longform.Diabetic$Group.rel ← relevel(as.factor(longform.Diabetic$Group), ref="MBCT")
longform.Diabetic$Gender.rel← relevel(as.factor(longform.Diabetic$Gender), ref="Female")
longform.Diabetic$Education.rel←relevel(as.factor(longform.Diabetic$Education), ref="High Education")
longform.Diabetic$Type_diabetes.rel←relevel(as.factor(longform.Diabetic$Type_diabetes), ref="Type II")
longform.Diabetic$Comorbidities.rel←relevel(as.factor(longform.Diabetic$Comorbidities), ref= "No")
#5.Cleaning long-form data
longform.Diabetic← longform.Diabetic[!names(longform.Diabetic) %in% c("Group","Gender","Education",
"Type_diabetes","Comorbidities")]
#6.Fitting random slope and intercept model
summary(fitted.model← lme(BDIscore ~ Group.rel + Gender.rel+ Age + Education.rel + Type_diabetes.rel + Comorbidities.rel + Neuroticism + Month,
{\tt random} \;\; \hbox{$=$} \;\; 1 + {\tt Month|ID, \;\; data=longform.Diabetic, \;\; control= \; lmeControl(opt="optim")))}
```

#### **SAS**

```
*Importing data;
□ proc import datafile="C:/Users/bushr/OneDrive/Desktop/Diabetic.csv"
             out=Diabetic dbms=csv replace; getnames=yes;
 run;
 *Testing the normality of the value;
-proc univariate data=Diabetic;
     var BDIscore;
     histogram / normal;
 run;
 *Fitting random slope and intercept model;
-proc mixed data=Diabetic covtest;
     class Group (ref="MBCT") Gender (ref="Female") Education (ref="High Education") Type diabetes (ref="Type II")
 Comorbidities (ref="No");
     model BDIscore=Group Gender Age Education Type diabetes Comorbidities Neuroticism Month/solution;
     random intercept Month/subject=ID type=un;
 run:
```

#### **Reference:**

[1] National Institute of Diabetes and Digestive and Kidney Diseases. "Diabetes Statistics - NIDDK." National Institute of Diabetes and Digestive and Kidney Diseases, Jan. 2024, www.niddk.nih.gov/health-information/health-statistics/diabetes-statistics#:~:text=Estimated%20prevalence%20of%20diabetes%20in.

[2] Life Line Screening. "What's the Difference between Type 1 and Type 2 Diabetes?" Www.lifelinescreening.com, www.lifelinescreening.com/health-education/diabetes/type-1-type-2-diabetes?sourcecd=WNAT003.

[3] Egede, Leonard E., and Charles Ellis. "Diabetes and Depression: Global Perspectives." Diabetes Research and Clinical Practice, vol. 87, no. 3, Mar. 2010, pp. 302–312, www.sciencedirect.com/science/article/abs/pii/S0168822710000471, https://doi.org/10.1016/j.diabres.2010.01.024.

[4] Elias, Daniel. "Free Works Cited Generator [Updated for 2021]." MyBib, www.mybib.com/tools/works-cited-generator.