Testing Individual vs Group Mean Differences in Social Science Research: A Multilevel Approach

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The article points out the disparity in findings when only testing group mean differences over time rather than individual differences over time. Too often individual differences are masked within the group mean thus not identifying individual changes. The results using the general linear model and multilevel regression models with an example clarifies this discrepancy in analyzing and interpreting social science research.

Past research applications have consistently tested mean group differences. This is commonly done in *t*-tests, analysis of variance, and analysis of covariance applications, among others. The experimental design, for example, conducts a test of control group versus experimental group mean differences using analysis of variance statistical tests (Maxwell & Delaney, 2004). This methodology is also referred to as a randomized clinical trial when testing for group mean differences (Machin & Fayers, 2010). Oftentimes a true experimental design is not possible, so the researcher uses a quasi-experimental design. A quasi-experimental design uses a comparison group rather than a control group. The typical quasi-experimental design considers a pre-test measure, followed by treatment, and then a similar post-test measure for the subjects in the comparison group and the experimental group. In the statistical analysis, individual post-test mean differences are adjusted for individual pre-test mean differences to control for bias. This adjustment is referred to as analysis of covariance and expressed in the general linear model as:

$$Y_{\text{Post}} = b_0 + b_1 X_{\text{Pre}} + e \ ;$$

where:

Y_{Post} = post-test measures
X_{Pre} = pre-test measures
b_0 = estimated sample intercept
b_1 = estimated sample regression weight, and
e = residual error.

The computation of the adjusted post-test group means is shown as (Hinkle, Wiersma & Jurs, 2003, p. 504):

$$\bar{Y}_k^i = \bar{Y}_k - b_w(\bar{X}_k - \bar{X})$$

where:

$\bar{Y}_k^i$ =adjusted group mean on the dependent variable (post-test measure)
$\bar{Y}_k$ =original group mean on dependent variable (post-test measure)
b_w =pooled within group regression coefficient
$\bar{X}_k$ =group mean on the covariate (pre-test measure)
$\bar{X}$ = grand mean on the covariate (pre-test measure)

The analysis of covariance methodology however has been criticized for several reasons. One important reason is that the assumption of a linear relation between the covariate variable (pre-test measure) and the dependent variable (post-test measure) is rarely met. Another reason, is that the research question no longer relates to the original post-test group mean differences, rather interprets the adjusted post-test mean differences (Tracz et al., 2005). These authors contended that the analysis of covariance approach changes the hypothesis, Type I error, and interpretation.

There are further drawbacks in only testing for mean differences between groups, whether adjusted or not. One reason is the selection of comparison group subjects, e.g. matching, blocking. A popular approach termed propensity score matching (Polkinghorne et al., 2004; Holmes, 2014) has proven useful in choosing cohort subjects for the comparison group. Another important reason is that individual differences can mask the average mean values obtained in each group. Some subjects may improve given treatment, others might stay the same, or some subjects may decline. These individual subject outcomes would not be identified when only testing for group mean differences.

Researchers using the general linear model have expanded testing only mean differences to comparing slope differences between two or more groups using separate regression equations. The null hypothesis in an experimental versus control group design would be specified as Ho: $\beta_{control} = \beta_{experimental}$, where β is the population regression slope coefficient of each group. The permits an *F*-test to determine the statistical significance between the two regression model R^2 values. If the *F*-test is statistically significant then the regression slopes of the two regression lines would be significantly different. The *F*- test for difference in R^2 values is given by:

$$F = \frac{(R_1^2 - R_2^2)/df_1}{(1 - R_1^2)/df_2}$$

Although this analysis is relevant in testing whether change (slopes) between the two groups (control and experimental) are statistically significantly different, it still does not indicate individual subjects change over time. Our interest is not in testing the group mean difference or slope difference, rather determining individual subject change over time. We therefore approach the problem differently by computing a separate regression equation for each subject. This can be accomplished using the general linear model or multilevel regression model application.

The general linear model equation yields a R^2 value which is interpreted as a variance accounted for effect size (Schumacker, 2015). This is appropriate when testing for a linear trend over time. If a subject's dependent variable increases over time but then decreases over time after treatment, a curvilinear trend is present. In this instance, the eta-squared (η^2) or partial eta-squared ($\eta^2_{Y1.12}$) is appropriate for a non-linear trend over time (Pedhazur, 1973). In many instances, $\eta^2 = R^2$ when linear. The variance explained in the treatment outcome from a general linear model equation is tested for statistical significance using the *F*-test (Hinkle, Wiersma & Jurs, 2013). The *F*-test is given as:

$$F = \frac{R^2/k}{(1 - R^2)/(n - k - 1)}$$

where:

R^2 = multiple correlation squared
k = number of predictor variables
n = sample size

The *F*-test is simultaneously testing whether all the regression coefficients (b values) are statistically significant in the equation. Individual subject slope values are not interpreted. We therefore propose the testing of whether individual subject *b* values are significant using the general linear model, that is statistically different from zero while controlling for the effects of the other predictor variables (Pedhazur, 1973). The general linear regression model can calculate individual regression coefficients to indicate change due to treatment. The general linear model *b* coefficient computation can be expressed in matrix form as:

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\mathbf{y}$$

where:

b = column vector a (intercept) plus b_k regression coefficients
X = *n* by 1 + k matrix with unit vector and *k* column vector of scores
$\mathbf{X}'$ = transpose of matrix **X**
y = *n* by one column of dependent variable scores
$(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}$= inverse of $(\mathbf{X}'\mathbf{X})$

A test of the statistical significance of the individual subjects *b* regression coefficients is obtained by:

$$t = \frac{b}{SE_b}$$

The general linear model has been used for testing slope differences or rate of change in repeated measure designs (Schumacker, 2015). Therefore, testing only mean differences (intercepts) has been expanded using the general linear model to include testing for slope differences, i.e. differences in the rate of change. Newman & Schumacker (2012) demonstrated the use of regression-discontinuity techniques to test for slope differences, intercept differences, and to examine change in individuals. In past developments, researchers have applied discrete-time survival analysis techniques to investigate the duration and timing

of event occurrence (Singer & Willett, 1993). The modeling of change and event occurrence has become more popular over the years in the statistical analysis of data (Singer & Willett, 2003).

The interpretation of an individual's change over time should have a more meaningful application in statistical analysis. The key design issue in testing for individual change is that it requires three measures over time, hence the basic pre-test and post-test design does not yield important subject change interpretations. The regression coefficients however can provide a meaningful individual interpretation. A positive *b* coefficient would indicate an increase, a negative *b* coefficient would indicate a decrease, and a zero *b* coefficient would indicate no individual change.

Bickel (2007) provided data examples for different multilevel regression models. Basically, when ordinary linear regression is not suitable, then the general linear model can be expanded to capture the various nested design effects. Moreover, the ability to estimate intercept and slope differences in individuals or groups is possible in multilevel regression models. Ordinary least squares is still used as a base model, after which multilevel regression models are added.

Regression Analysis

The regression approach involves computing the intercept and slope of each subject using separate general linear model equations. A regression program was written using `R` (R Core Team, 2020) to estimate individual regression coefficients and is listed in the Appendix. The regression program computes a subject's regression coefficient over repeated measures. The statistical analysis can therefore report individual subject coefficients, standard errors, test of statistical significance, and level of statistical significance (*p*-value). The general linear model equation can be expressed as:

$$Y_i = b_0 + b_1 X_i + e_i \ ;$$

where:

Y_i = individual measures
X_i = individual subject treatment time
b_0's = estimated individual subject intercept coefficients
b_i's = estimated individual subject slope coefficients, and
e_i = residual error

Multilevel Analysis

Multilevel analysis is an extension of several regression models. For example, in *R*, the expression: `lm(y ~ x)` or `lmer(y ~ x)` is the base linear regression model. Next, the expression: `glm(y ~ x, family = binomial)` is the extension to the general linear model. The expression: `lmer(y ~ x + (1|group))` is the extension to a multilevel model with *group* as the nested effect. The `lmer` function is seen as the `lm` function for multilevel modeling applications. Finally, `glmer(y ~ x + (1|group), family = binomial)` is the extension for the general linear multilevel model. These expressions clearly show the regression model extensions to multilevel modeling.

Multilevel modeling extends ordinary least squares (OLS) regression models to models that have additional variance terms for handling non-independence due to group membership. The OLS regression models assume that the relationship between the independent variable and dependent variable is constant across groups. This assumption is generally tested using a scatterplot and/or the ICC interpretation (Shrout & Fleiss, 1979). The key to multilevel models is to understand how nesting individuals within groups can produce additional sources of variance in the data.

The first variance term that distinguishes a multilevel model from an OLS regression model is a term that indicates the degree to which groups differ in their mean values (intercepts) on the dependent variable (τ_{00}). Group-level variables differ across groups but are consistent for individuals within the same group. For example, a group-level variable could be used to predict group-level variance (τ_{00}) in treatment outcomes between experimental and control groups.

The second variance term that distinguishes a multilevel model from an OLS regression model is a term that indicates the degree to which slopes between independent and dependent variables vary across groups (τ_{11}). Multilevel models permit testing whether the slope values vary between groups. If slopes vary between groups, then we know that the rate of change is different. For example, the treatment outcome desired occurs faster in one group than another.

A third variance term is common to both multilevel models and OLS regression models. This variance term, σ^2, reflects the degree to which an individual score differs from its predicted value within a specific group. These are considered level-1 values in the multilevel model equation. Level-1 variables differ among members of the same group.

The multilevel regression model with intercept (γ_{00}) and slope (γ_{11}) estimation is shown as:

$$Y_{ij=}\gamma_{00} + \gamma_{11}X_{ij} + U_{ij} + e_{ij}$$

Multilevel regression models can include fixed or random intercept and slope variance estimation. We are only interested in conducting level-1 individual intercept and slope differences.

Methods and Procedures

Data and Method

An experimental design would randomly assign subjects to a control group and an experimental group. A heuristic data set was created with the first five subjects in the control group (1 to 5) and the last five subjects in the experimental group (6 to 10). The heuristic data set of 10 subjects has six (6) smoking measures per subject as shown in Appendix. The data set shows the 6 measurements for each group with 3 measures before treatment and 3 measures after treatment. Treatment consisted of counseling to quit smoking for subjects in the treatment group and a distribution of stop smoking pamphlets in the control group.

Our interest was in computing individual subject intercept and slope regression coefficients over time. In the regression analysis (*R* program in Appendix), it is hypothesized that the control group subjects who received only a stop smoking pamphlet would indicate no increase or a modest change (not statistically significant), while the experimental group subjects would have a statistically significant decrease in smoking after counseling, hence negative slope coefficients. In the multilevel regression analysis (*R* program in Appendix) we compared the baseline model to the intercept only model and the intercept and slope model. The group effect for experimental versus control was not included in the analysis to better demonstrate individual change. The multilevel regression model comparisons indicate how the base regression model is compared to models that test intercept only and both intercept and slope.

Results

Multiple Regression Analysis

The individual subject regression analysis provided individual subject intercept and slope values. The results in Table 1 indicated that 4 out of 5 subjects in the control group did not change significantly, while each subject in the experimental group did show a decreased change in smoking.

Table 1. Subject Intercept and Slope Regression Coefficients

Subject	Group	Intercept	Slope	*SE*	*t*	*p*
1	Control	83	-0.14	1.39	-0.10	0.92
2	Control	81	-0.14	1.56	-0.09	0.93
3	Control	86	-0.28	1.45	-0.19	0.85
4	Control	90	-6.85	0.38	-17.73	0.0001
5	Control	78	1.42	1.18	1.21	0.29
6	Experimental	55	-7.57	0.50	-15.09	0.0001
7	Experimental	71	-10.71	0.41	-25.98	0.00001
8	Experimental	49	-7.42	0.50	-14.81	0.0001
9	Experimental	70	-10.00	0.0005	-19.23	0.00001
10	Experimental	81	-10.71	0.42	-25.98	0.00001

The results permit a determination of whether any subject in either group increased or decreased their smoking behavior. Our example showed that the slope values decreased significantly for subjects in the treatment group. One subject (ID = 4) in the control group decreased smoking behavior significantly after receiving a quit smoking pamphlet. Individual statistical analysis would clearly show better results for interpretation than simply testing group mean differences. The regression coefficients listed in Table 1 can be displayed using a simple EXCEL scatter plot (Figure 1) that visually displays their slope values, where *b*-values above and below a 0 value would indicate change.

The issue is how can we analyze our research data to test for individual subject change due to treatment rather than interpret only group mean differences. This can be accomplished by computing individual subject regression equations. The general linear model can compute the intercept and slope for each subject. The intercept value for each subject can be interpreted as a baseline measure or starting point. The slope value for each subject can be interpreted as a rate of change. The computed individual subject slope value is divided by its standard error to compute a *t*-value with an accompanying *p*-value for statistical significance. The practical interpretation is readily available since a positive regression coefficient (*b*-value) indicates an increase in the measured outcome variable; a negative regression coefficient indicates a decrease; and a zero regression coefficient indicates no change. The regression coefficient interpretation can also be made in the context of change from an intercept value (baseline measure).

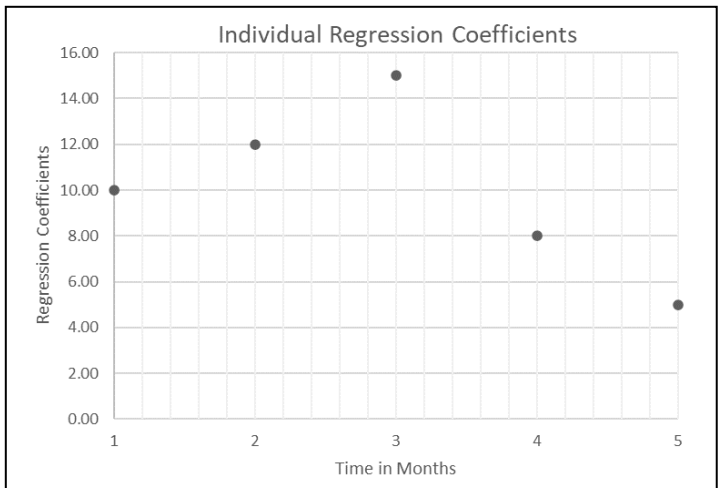

Figure 1. Excel Graph of Individual Regression Coefficients

Our results indicated a subject in the control group had a significant negative regression coefficient, thus changed. In contrast, all subjects in the experimental group had significant negative regression coefficients. We can therefore examine each individual subject to know whether one, a few, or all benefited in a study; thus, whether individual subjects change in either the control or experimental group can easily be tested and interpreted. This is more advantageous than simply having significant mean differences between groups where individual results are not readily interpreted.

Multilevel Analysis

The multilevel program `R` script in the Appendix compares three different multilevel model equations. The equations are expressed as:

```
Multilevel Models:
base: Y ~ (1 | Subject)
int1: Y ~ Time + (1 | Subject)
slope1: Y ~ Time + (Time | Subject)
```

The first equation (base) tests for a common intercept and common slope for all individuals. The second equation (int1) tests for intercept differences in individuals. The third equation (slope1) tests for intercept and slope differences in individuals across time.

A statistical comparison of the three multilevel regression equations indicated that there are intercept differences (int1: $p < 0.0001$) and slope differences (slope1: $p < 0.0001$). These results are output as:

```
Model  npar  AIC    BIC    logLik   Chisq        df     p
base      3 515.50 521.78 -254.75  509.50
int1      4 487.72 496.10 -239.86  479.72 29.777  1 0.00000004847
slope1    6 419.40 431.96 -203.70  407.40 72.328  2 0.0000000000000002
```

The results are presented in Table 2 for the three multilevel regression models. The level-1 individual prediction error was less for the intercept and slope model (σ^2 reduced from 169.17 to 16.65) and ICC increased from 0.80 to 0.98.

A comparison of the individual person intercepts and slopes across time is displayed in Figure 2. The `R` script for graphing the individual intercepts and slopes is in the Appendix. The individual graphs clearly show that individuals do not have a common intercept and slope (base regression model), nor a common intercept with varying individual slopes (int1), rather different individual intercepts and slopes (slope1). The individual graphs point out that individual treatment varied among patients across time.

Table 2. Multilevel Model Comparisons (Intercept and Slope – Time)

	Y			Y			Y		
Predictors	**Estimate**	**95% CI**	**p-value**	**Estimate**	**95% CI**	**p-value**	**Estimate**	**95% CI**	**p-value**
Intercept	58.17	41.15 – 75.18	<0.001	74.47	56.68 – 92.26	<0.001	74.47	66.26 – 82.67	<0.001
Time				-4.66	-6.13 – -3.18	<0.001	-4.66	-7.85 – -1.46	0.005
	Random Effects								
	σ^2	169.17			95.16			16.65	
	τ_{00}	693.84 $_{ID}$			706.18 $_{ID}$			153.00 $_{ID}$	
	τ_{11}							24.42 $_{ID.Time}$	
	ρ_{01}							0.62 $_{ID}$	
	ICC	0.80			0.88			0.98	
	N	10 $_{ID}$			10 $_{ID}$			10 $_{ID}$	
Observations		60			60			60	

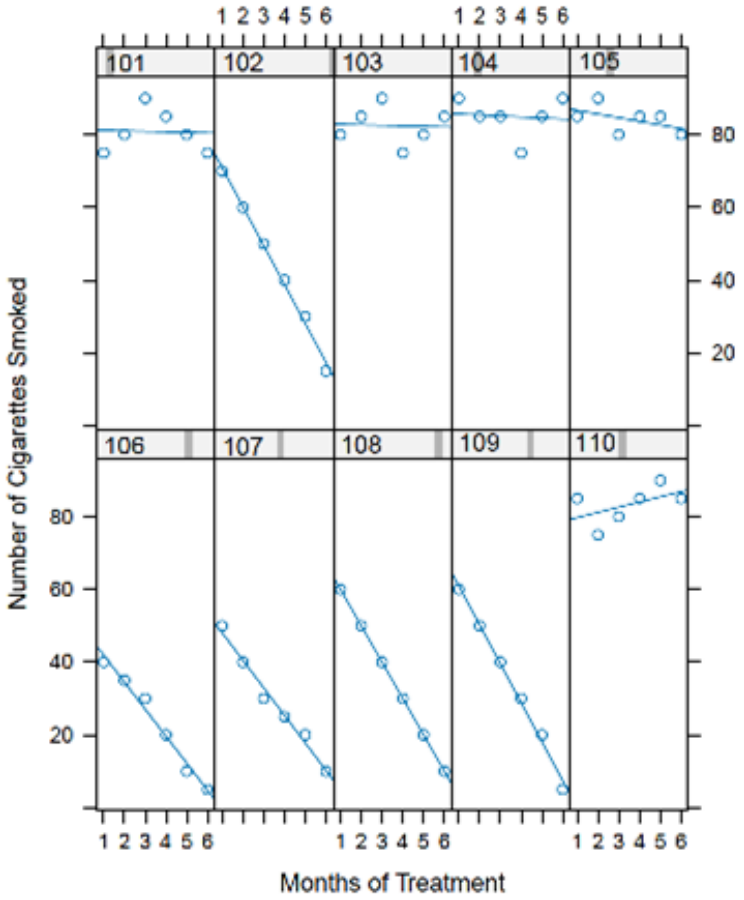

Figure 2. R plot of individual patient intercepts and slopes

Summary and Discussion

There have been a few statistical approaches used to analyze mean differences between groups, the most popular being *t*-test, analysis of variance; and analysis of covariance. There have been substantiated published articles over the past several decades criticizing the use of analysis of covariance. The use of analysis of variance in true experimental designs therefore has been the gold-standard of research designs. Unfortunately, researchers have not always been able to conduct true experimental designs and struggled with creating comparison groups in quasi-experimental designs. The use of an experimental design or a quasi-experimental design using propensity score matching for the cohort of subjects in a comparison group would indicate group mean treatment outcomes. However, the design analysis does not indicate individual subject treatment effectiveness.

Another emerging analysis method, regression-discontinuity, was developed for program evaluation (Trochim, 1984). This methodology was eventually extended to randomized clinical trials to test slope differences between control and experimental groups (Trochim, 1992). This proved to be a useful method to determine whether a program or treatment was effective. The test of slope differences between groups via regression-discontinuity however did not provide the individual subject treatment results. Individual change can still show individual gains, losses, or no change in treatment. The ability to examine individual subject treatment status can be deduced from a regression-discontinuity design if proper dummy coding of subject vectors is employed. This is generally not done in applied social research studies, so the emphasis is still not on the individual subject change, rather only group outcomes. For example, was a certain stop smoking program effective?

Multilevel modeling (Bickel, 2007; Schumacker & Lomax, 2016) has demonstrated the use of the general linear model and multilevel regression models to generate individual intercept and slope values across time. It is recommended that the intra-class correlation coefficient be interpreted to determine whether a common regression line or individual regression lines should be interpreted (Shrout & Fleiss, 1979). In addition, the *design effect* adjustment is used in some studies where cluster randomized control trials are conducted (Bland, 2004). The design effect uses the intra-cluster correlation ($D_{eff} = 1 + (m - 1)p$ to assess the effect of clustering, where m is the sample size in a cluster and p (ICC) is the intra-cluster correlation. Clustering may result in p-values and confidence intervals which are biased if cluster size is large, the number of clusters is small, or the intra-cluster correlation coefficient is large.

A SAS approach, varying time estimation method (VTEM), estimates regression coefficients in a time-varying effect model (TVEM SAS Macro, 2017). It provides an end user SAS macro (%VTEM) to make longitudinal analysis using regression equations easier to execute (Li, Dziak, Tan, Huang, Wagner, & Yang, 2017). This SAS macro permits fixed or time varying variables in the equations and highlights the pivotal work by Singer & Willet (1993; 2003) who earlier demonstrated SAS code for time varying variables in longitudinal data analysis. Additionally, the centering approach in VTEM, which is used in the graphical display of b-value deviations around zero (0) supports the earlier work by Aiken & West (1991). Basically, if the graph shows b-values with confidence intervals *not* capturing the zero point, then the fixed or time varying variable effect is statistically significant. The model selection fit function criteria are based on Akaike information criterion (AIC; non-parametric) and Bayesian information criterion (BIC - parametric), although VTEM is considered a non-parametric approach. These two fit functions are commonly used for choosing the best predictor subset models in regression where lower values suggest a model closer to a true model. A new *parametricness index* (PI) has been introduced to assess whether the best regression model selected should be judged by AIC or BIC fit criteria in estimating the regression function (Liu & Wang, 2011).

All of the aforementioned approaches are important techniques used to assess change over time. The importance of analyzing individual subject change over time needs a more prominent place in our social science research. It should be the most important practical question in longitudinal modeling. We feel that individual treatment effectiveness is more important than group mean or group slope differences. Several methods test group mean differences (t-test, analysis of variance, analysis of covariance); however, more suitable methods should be used that provide individual intercept and slope values (multilevel modeling, survival analysis, longitudinal analysis). The basic `R` programs in the Appendix makes it easy to compute individual subject treatment results over time. Any statistical analysis that masks individual contribution by only computing and interpreting group mean and/or group slope differences are not recommended.

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Appendix

Smoking Data (Heuristic Person-Period Data)

Control	Subjects			Treatment	Subjects
ID	**Y**	**Time**	**ID**	**Y**	**Time**
1	80	1	6	50	1
1	85	2	6	40	2
1	90	3	6	30	3
1	75	4	6	25	4
1	80	5	6	20	5
1	85	6	6	10	6
2	75	1	7	60	1
2	80	2	7	50	2
2	90	3	7	40	3
2	85	4	7	30	4
2	80	5	7	20	5
2	75	6	7	5	6
3	90	1	8	40	1
3	85	2	8	35	2
3	85	3	8	30	3
3	75	4	8	20	4
3	85	5	8	10	5
3	90	6	8	5	6
4	85	1	9	60	1
4	75	2	9	50	2
4	70	3	9	40	3
4	65	4	9	30	4
4	55	5	9	20	5
4	50	6	9	10	6
5	85	1	10	70	1
5	75	2	10	60	2
5	80	3	10	50	3
5	85	4	10	40	4
5	90	5	10	30	5
5	85	6	10	15	6

Regression Program R Script

```
# Smoking data
# Compute intercept and slope of each subject
# ID = subject id;   Y = number of cigarettes smoked ; Time = months of
treatment ( 1 to 6)
# CTRL = control ;TRT = treatment; CT = 1,2,3; TT = 4,5,6; P1 to P10 are
dummy coded
# Input data
mydata=read.table("c:/regression.csv",header=TRUE,sep=",")
mydata
# Compute individual intercept and slope values
# All subjects  ( i = 10 subjects)
K = 1
L = 6
for (i in 1:10) {
j = lm(Y[K:L] ~ Time[K:L],data = mydata)
z = summary(j)
print(z)
K = K + 6
L = L + 6          }
```

Note: Individual regression results copied into Table 1

Multilevel Model Program R Script

```
# Smoking data
# Compute intercept and slope of each subject
# Subject = patient id   Y = number of cigarettes smoked  Time =
months of treatment
# Input data

install.packages("tidyverse"); install.packages("sjPlot");
install.packages("lme4")
library(tidyverse);library(sjPlot);library(lme4)

# Read in data file

patient = read.csv("C:/regression.csv",header=TRUE,sep=",")
attach(patient)

# Base null model
base = lmer(Y ~ (1|Subject),data=patient)

# Intercept only model
int1 = lmer(Y~Time +(1|Subject), data = patient)

# Slope and Intercept model
slope1 = lmer(Y~Time + (Time|Subject),data = patient)

# Compare models
options(scipen=999)
anova(base,int1,slope1)

 # Table results
tab_model(base,int1,slope1)
```

Note: Multilevel Model results in Table 2

Multilevel Model Graph R Script

```
install.packages("lme4")
library(lme4)
require(lme4)
require(lattice)

patient = read.csv("C:/Documents/Articles2024/Multilevel Model
Article/regression.csv", header=TRUE, sep=",")
attach(patient)

xyplot(Y ~ Time | Subject, patient, type = c("p","r"),
       index = function(x,y) coef(lm(y ~ x))[1],
       xlab = "Months of Treatment",
       ylab = "Number of Cigarettes Smoked", aspect = "xy")
(fm1 <- lmer(Y ~ Time + (Time|Subject), patient, subset=Time >=0))
```

Note: Multilevel Model Graph Output in Figure 2