Mixed-Effects Location Scale Models on Health Behaviors to Academic Performance via Affect: Modeling Variances

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Abstract

Ecological momentary assessment (EMA) data collection is a tool that allows subjects to report the momentary state of the variables in their real-time environment repeatedly. In the study of "How Health Behaviors Relate to Academic Performance via Affect: An Intensive Longitudinal Study", the investigators implemented EMA data collection, studied the between-person level and within-person level using mixed-effects regression models and achieved some significant results [14]. For this study, we aim to conduct a more extensive analysis on their data by modeling the variances using mixed-effects location scale model, a model that permits subjects to vary their means (location effects) and subjects' variability (scale effects). By implementing this model to this existing study, some novel findings are discovered. We conclude that daily higher level of negative affect is associate with more erratic learning goal achievement.

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1 Introduction

Sleep and physical activity habits of young people, especially students, have become a larger subject of study more recently. In a study that linked sleep habits with academic performance, Dewald et al. [9] discovered that among children and adolescents, the correlation coefficient between sleep quality and academic performance is 0.096, and the correlation between sleep duration and academic performance is 0.069 in their meta-analysis. Other sleeping problems such as sleep disorders and sleep difficulty also have harmful impacts on college students' academic performance [29][15].

Physical activity has also been implicated in academic performance. A recent study has found that female college students with higher body mass index (BMI) is associated with worse school performance in Saudi Arabia [2]. Likewise, a cluster randomized controlled trial among 14-year-old teens demonstrated that the intervention groups with extra two hours exercises per week for over nine months have significantly higher performance in numeracy and reading compared to control group [35]. When considering factors that lead to students exercising, recent research evidenced that the external environment, including students' important relationships, such as family, friends, and stress from society, are key motivators for college students to exercise [13].

1.1 Summary of the original study

In the study of "How Health Behaviors Relate to Academic Performance via Affect: An Intensive Longitudinal Study" authored by Flueckiger1 et al. [14], researchers performed an analysis to test how sleep quality and physical activity were correlated with student's mood affect and academic performance during a pressured exam time frame. The data was obtained from a survey of 82 first-year psychology students from the University of Basel in Switzerland. These participants were told to complete an online questionnaire for consecutive 46 days over the exam period and report their exam as pass or fail at the end of the study. Participants were only approved to study psychology upon passing all six exams. Participants were allowed to retake each exam a single time if needed. Since post-examination period happened in the last 14 days, and 10 students did not take the exam or report the exam grades, this dataset then only included data from first 32 days and the remaining 72 students. In the survey, participants were required to answer online questionnaires every day on their sleep quality, physical activity, positive and negative affect, learning goal achievement, and report examination grades at the end of study. Rather than using a binary exam score (pass/fail) that could only be obtained at the end of study, learning goal achievement was collected as a response measurement because it could be obtained daily.

Results indicated that during a test period, students with greater overall learning goal achievement are predicted by better overall sleep quality, but not physical activity. Students have greater chance to pass the exam if they kept higher average learning goal achievement level. Positive affect is a mediator between sleep quality and physical activity with average learning goal achievement. Moreover, in a study of daily levels, participants who experience better sleep quality achieve better learning goals on the same day. Daily sleep quality and physical activity on learning goal achievement are both mediated by daily positive and negative affect, as well [14].

1.2 Directions for following sections

In the next section, we will present a literature review. First, the mediation model and ecological momentary assessment (EMA) approach will be introduced and some examples will be provided. Next, we will discuss mixed-effects location scale model and method to check the consistency of the original analysis. Results will then be displayed.

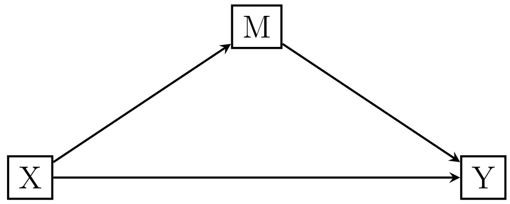
2 Literature Review

2.1 Mediation model

Mediating variables have been widely used in psychology in recent years to convey the relationship between covariates and response variables. To understand the frequency of mediation in psychology, MacKinnon et al. [25] searched for the number of articles with "mediation" as a keyword or that have cited Baron & Kenny [4] (the most cited paper that outlines mediation methods) through the *PsyInfo* search engine; 291 references were found, ranging from social psychology (98 articles), clinical psychology (70) and health psychology (29).

2.1.1 Simple mediation model

The simplest mediation model is the single-mediator model, where X does not have to be the actual predictor for response Y; a mediator M can explain relationship of X and Y. Mediation contains the following three regression models:



$$\text{Step 1: } Y = b_0 + b_1 X + e$$

$$\text{Step 2: } M = b_0 + b_2 X + e$$

$$\text{Step 3: } Y = b_0 + b_3 X + b_4 M + e$$

In step 1, a normal regression analysis is used to test the relationship between X and Y. If b_1 is significant, we proceed — this is total effect. If it is not significant, but we believe there are reasons that they are related, we can still continue to step 2. In step 2, we examine the relationship between X and mediator M. Detecting b_2 as significant implies that the mediation model works. In step 3, when including both independent variable X and mediator M into the model, a full mediation between X and Y occurs when X causes no effect on Y. A partial mediation between X and Y occurs when the effect of X on Y remains, but in a smaller magnitude. In step 3, we see that b_3 is the direct effect. Mediation effect (or indirect effect) is calculated by $b_1 - b_3$, which is equivalent to $b_2 * b_4$. A mediation analysis aims to determine if this indirect effect is statistically significant [21].

2.1.2 Mediation models in academic performance

Academic performance is one of many indicators for student success, and can be measured by GPA score. Many recent studies have investigated predictive factors that contribute to higher academic performance. Robbins et al. [33] have studied that achievement motivation and academic self-efficacy is the strongest psychosocial predictors for GPA score. Furthermore, a meta analysis has summarized that personality traits, self-regulatory learning strategies, motivational factors, psychosocial contextual influences, and approaches to learning are five main aspects associate with GPA [32].

Mediation variables have popularly been studied in analyzing students' academic performance. According to our search, mediation variables can be categorized into two types: 1. psychological factors, 2. environmental factors.

Psychological factors

It is reasonable to assume that a positive attitude can lead to better academic achievement, while anxiety and depression can result in the opposite. However, two sensitivity analyses done by Rogaten and Moneta [34] have displayed different answers. Creative cognition mediates the trait intrinsic motivation's positive effects and adaptive meta-cognition, which then increases academic performance. Thus, the study shows that positive attitude alone is not the only predictor of high performance. In addition, the influence of anxiety as a mediator between fear and test performance appears to be nonsignficant in the 2015 article by Embse, Schultz and Draughn [38], which is contrary to our assumptions.

One longitudinal study observed an association between grit and performance in academic when via self-efficacy, and it is found self-efficacy is a useful mediator in e-learning performance for college students during the COVID-19 pandemic [37].

Environmental factors

Physical activity, sleep quality, and external supports are some mediators affecting academic performance. One study looked into the relationship between Body Mass Index (BMI) and Grade Point Average (GPA) among college female students and found that academic self-efficacy is a partial mediator between them [1]. In addition, sleep quality is another critical factor affecting academic performance. O'Hare et al. [28] conducted a cross-sectional research among children aging between six and ten and concluded sleep difficulties is correlated with impaired academic performance via sluggish cognitive tempo and daytime sleepiness. Lastly, obtaining external supports, such as from parents and teachers, have also been tested and determined as significant mediation variables between metacognitive awareness and schoolwork [5]. During the pandemic, similar results have been discovered to lessen Malaysian university students' stress related to employment and finance via university and lecturer support [27].

It must be noted that there are a few limitations here. Majority of the articles we found are cross-sectional, so it is very difficult to show causation. Future longitudinal studies should be considered. Other frequently mentioned limitations in these articles are convenience sample and unbalanced gender participants, which can be resolved through further study.

2.2 Ecological Momentary Assessment data

2.2.1 Limitations of traditional longitudinal studies

There have been numerous studies to investigate student health behaviors in recent years. However, most traditional longitudinal studies only collected a single or a few data points per individual, which ignores the individual's variability trend over time [10], which in turn fails to capture the real-time status of the subjects [12].

2.2.2 Advantages of EMA approach

To address this issue, ecological momentary assessment (EMA) has recently become more attractive in medical research [11]. EMA data is a tool with which subjects report their momentary state of the selected variables in a real-time environment repeatedly [6]. This approach highly improves the accuracy of the data and minimizes the retrospective bias [12].

Due to the nature of the collection approach, there are usually abundant data points (about to 30 or 40 observations per subject) being collected through EMA [20]. After obtaining these data, exploring how subject levels differ compared to others (between-subject variability) and how each subject varies over time (within-subject variability) becomes possible [22]. Another benefit to using EMA is that, as technology becomes more accessible to our daily lives, it is very easy to collect data through mobile devices. We found a systematic review in studying the feasibility in smartphone-based EMA in well-being research, and 53 reviewed articles concluded that this approach is feasible for measuring the variation of well-being under various circumstances [7]. A similar meta analysis in depression studies has also indicated that a technology-based EMA approach can provide better ecological validity and precision, as well as produce better customized interventions to broader groups who normally do not receive them [8].

2.2.3 Examples

Several recent studies have implemented the EMA approach to study the variability of certain behaviors common in mood across various populations. In a pilot study examining the effects of duty status on acute stress and tiredness in firefighters [6], using EMA approach to record data by smartphone is viable, and when they are on-duty, similar stress levels and tiredness outcomes are found compared to when they are off-duty. Another result obtained was that firefighters who have less consistency level in stress and tiredness tend to have higher average stress and tiredness. A second study that applied the EMA method is studying what factors influence adolescents' sedentary time; staying alone and indoors predict higher average and more stable sedentary time [22]. An adolescent study about their mood variation on smoking behavior was conducted by Hedeker et al. [18] and concluded that when adolescents smoke, they report higher positive affect and lower negative affect than they do not smoke at random times.

In terms of this present study, to our knowledge, no previous studies have used EMA data to specifically model the variance in order to explore the association between health behaviors and students' academic success via affects. Given that the original investigators used the EMA approach to collect data, we aim to conduct a more extensive analysis by modeling effects on the variability of the outcomes. We model the effects after having checked the current results' consistency compared to the original analysis.

3 Methodology and Models

3.1 Consistency of original analysis

Before performing the current analysis, we reproduce the analysis reported in the original paper. Software **Stata** (Statistical software for data science) assists analysis. Specifically, multilevel mixed-effects linear regression model (**mixed**) is used for building mediation and full models separately. Secondly, multilevel mediation models (**gsem**) compute the total and direct effects. The parameters we obtained at first were drastically different from the original paper. We then contacted the authors and they provided us with the original codes written in German. By using their variables transformations, we are able to reproduce their analysis.

3.2 Mixed-effects regression model

One constraint for using a simple linear regression model in longitudinal data is that it is not rational to assume independent and normally distributed errors. Because subjects are measured repeatedly, errors within each subject should exhibit some correlations. Another reason is that the simple linear regression model does not allow individuals to change as time goes on. For these reasons, using a mixed-effects regression model permits us to include individual-specific effects within the model, which accepts that subjects to vary across time [16].

To address this issue, a mixed-effects regression model is implemented to exhibit the influence of each subject on their repeated outcomes in the original model and can be written as following: for measurement y of individual i ($i = 1, 2, ..., N$ individuals) on occasion j ($j = 1, 2, ..., n_i$ occasions):

$$Y_{ij} = x_{ij}^T \beta + v_i + \epsilon_{ij}, v_i \sim N(0, \sigma_v^2), \epsilon_{ij} \sim N(0, \sigma_\epsilon^2) \tag{1}$$

where x_{ij} is p x 1 vector of fixed effects regressors and β is the corresponding p x 1 fixed effects parameters. v_i is the random effects and ϵ_{ij} is the residual vector [11]. In the original study analyses, researchers used random-intercept effect on different subject level. In short, multiple parallel lines are drawn from each participant to the overall average trend among all participants. It is worth noting that the magnitude of the variance σ_v^2 depends on the subjects' heterogeneity, and σ_v^2 and σ_ϵ^2 are equivalent across all individuals from the dataset.

3.3 Mixed-effects location scale model

In studies of intensive sampling methods, such as ecological momentary assessment, **MixWILD** (Mixed model analysis With Intensive Longitudinal Data) allows us to assess the effects of subject-level parameters (variance and slope) of time-varying variables. This is a user-friendly graphical user interface (GUI) that does not require command-line interface to do the analysis. Using the expectation-maximization (EM) algorithm and the Newton-Raphson solution, MixWILD performs maximum likelihood estimation calculations in FORTRAN. By using empirical Bayes equations, one can estimate the mean and variance of the subject's random effects [11].

In our analysis, MixWILD is used to conduct the analysis on the mixed-effects location scale model (MELS), where location effect reflects random subject's mean, and scale effect reflects random subject's variability [11].

Expanding from the original model, a more complicated model is proposed in Hedeker and Mermelstein's paper [17]. For measurement y of subject i ($i = 1, 2, ..., N$ subjects) on occasion j ($j = 1, 2, ..., n_i$ occasions):

$$Y_{ij} = x_{ij}^T\beta + v_i + \epsilon_{ij}, v_i \sim N(0, \sigma_{v_{ij}}^2), \epsilon_{ij} \sim N(0, \sigma_{\epsilon_{ij}}^2) \tag{2}$$

where

$$\sigma_{v_{ij}}^2 = \exp(u_{ij}^T\alpha) \tag{3}$$

and

$$\sigma_{\epsilon_{ij}}^2 = \exp({w_{ij}}^T\tau + \tau^* v_i + \omega_i), \omega_i \sim N(0, \sigma_\omega^2) \tag{4}$$

- β are effects on mean
- α effects on BS variance
- τ effects on WS variance
- τ^* is linear association between mean and WS variance
- v_i and ω_i are random location and scale effects (assumed normally distributed)

Similar to mixed-effects regression model, x_{ij} is the p x 1 vector of regressors and β is the corresponding p x 1 vector of regression coefficients in the mean model (Equation 2). In mixed-effects location scale model, we also model the between-subject (BS) variance $\sigma_{v_{ij}}^2$ (Equation 3), which reflects the degree of heterogeneity between subjects. Instead of assuming constant variance across subjects, BS variance allows us to take into account covariates u_{ij} via coefficient α. To achieve positive variances, the exponential function is provided in the program.

Likewise, an exponential function is used to show for WS variance in equation 4 for detecting erraticism within subjects. One can model WS variance by fixed-effects covariates w_{ij} via coefficients τ. Moreover, v_i indicates subject's mean and ω_i indicates each subject's variability with regard to their own mean. We call v_i and ω_i random location and scale effects and assume they are normally distributed. Note that v_i and ω_i do not have to independent. They exist some correlations. The distribution between v_i and ω_i is

$$\begin{pmatrix} v_i \\ \omega_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{v_{ij}}^2 & \sigma_{v\omega} \\ \sigma_{v\omega} & \sigma_\omega^2 \end{pmatrix}\right)$$

where $\sigma_{v_{ij}}^2$ and σ_ω^2 are the variances of v_i and ω_i, and $\sigma_{v\omega}$ is the covariance between v_i and ω_i.

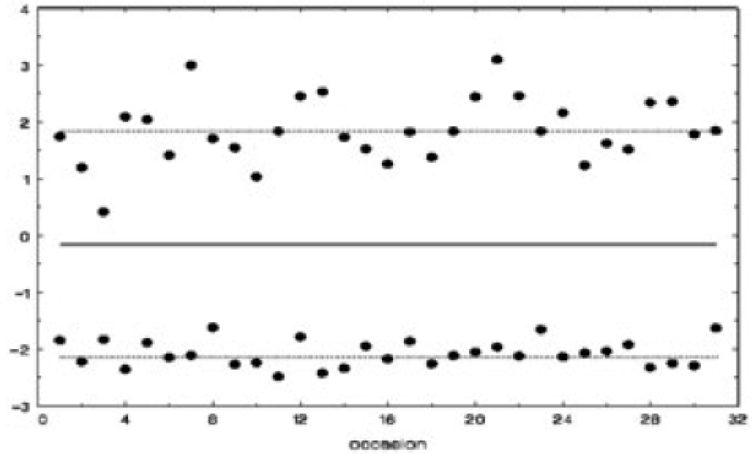


Figure 1: Method Illustration [20]

Figure 1 provides a small visual example for the model, which can be referred to in Hedeker et al.'s paper [20]. The middle solid line is the average across all individuals in the data. Covariates x determine the position of this mean line via β coefficients. The two dashed lines display an instance of two random participants' average mean. In reality, the number of dashed lines is equivalent to the sample size. The differences between these two lines is BS variances $\sigma^2_{v_{ij}}$. A larger BS variance is found if subjects are away from the average mean or vice versa. Regarding WS variance, the spread of the each subject is depicted visually. The subject above the average has bigger WS variance (i.e. more erratic) compared to the subject below the average. Furthermore, errors that were captured by covariates in WS variance model is left by a random scale effect ω_i. Note that random effect v_i and ω_i are correlated with covariance parameter $\sigma_{v\omega}$. This represents the relationship between subject's mean and their WS variance. In this example, a positive relationship is found because the person with higher mean also has greater WS variance.

To observe how these models are fitted in MixWILD, we take the model between physical activity and academic performance via negative affect as an example. Specifically, we look at mediation model here. The outcome variable we look at is negative affect (NA) and the regressors we include in equation 2 mean model are time variables (week, week^2, week^3) and physical activity (physAct). Quadratic and cubic terms of time are included in the original paper to determine whether there is a nonlinear time trend of the outcome variables. It is also worth mentioning that in order to gain a reasonable change across time, day is centered and scaled to exhibit average change across weeks per unit, which ranges from −2.21 to 2.21. This is how we get the time-varying covariates week. We also include each student's average physical activity, which is what we called between-subject level $\overline{physAct_i}$. Within-subject level $physAct_{ij} - \overline{physAct_i}$ represent students' daily level, which is calculated by subtracting students' average physical activity from every day physical activity level. Regarding equation 3 between-subjects (BS) variance submodel, the only predictor is week. Week, physical activity (both between-subject level and within-subject level) are the variables included in within-subject (WS) variance submodel (equation 4). Expanding from that, table 1 summarizes the parameters on the full model using learning goal achievement (LGA) as outcome variable as well.

Models	Outcome	β (mean model)	α (BS variance)	τ (WS variance)
Mediation model	NA	week, week^2, week^3 $\overline{physAct_i}$ $physAct_{ij} - \overline{physAct_i}$	week	week $\overline{physAct_i}$ $physAct_{ij} - \overline{physAct_i}$
Full model	LGA	week, week^2, week^3 $\overline{physAct_i}$ $physAct_{ij} - \overline{physAct_i}$ $\overline{NA_i}$, $NA_{ij} - \overline{NA_i}$	week	week $\overline{physAct_i}$ $physAct_{ij} - \overline{physAct_i}$ $\overline{NA_i}$, $NA_{ij} - \overline{NA_i}$

Table 1: Model parameters for Physical Activity (physAct) on Learning Goal Achievement (LGA) via Negative Affect (NA)

Similar approaches are implemented to three other models, which use combinations with the replacements of sleep quality (SQ) to physical activity (physAct) and positive affect (PA) to negative affect (NA).

4 Results

4.1 Descriptive statistics

Binary Variable	Count	Total count %
Sex (n = 62)		
Female	54	87
Male	8	13
Exam (n = 72)		
Pass (1)	34	47
Fail (0)	38	53

Table 2: Descriptive Statistics

Continuous Variable	n	Mean	SD	Median	Range
Age	62	23	5.79	21	17-51
Semester	62	2.93	1.89	2	1-10
Sleep quality	72	2.99	0.80	3	1-4
Physical activity	72	331.03	413.68	180	0-3960
Positive affect	72	4.18	1.61	4.33	1-7
Negative affect	72	2.65	1.48	2.33	1-7
Learning goal achievement	72	2.16	1.08	2	0-4

Table 3: Descriptive Statistics Continued

Table 2 and table 3 show descriptive statistics of the data after removing the missing values for each individual variable from the dataset. Sixty-two students are included and 87% are female students. Slightly fewer than half of them (47%) passed the exam.

Age range of the participants is large, from 17 to 51, with a median age of 21. Similarly, in semester, the median is that students were in their second semester during the time the survey was conducted, with an outlier of participants in their 10th semester. Sleep quality, physical activity, positive affect, negative affect and learning goal achievement are evaluated from the lowest (Not at all) to highest (Completely). Note that among these measurements, besides physical activity, Likert scale were used. Mean and median in sleep quality are same with a score of three. Positive affect reported scores are higher than negative affect, both on average and median with a similar level of spread based on standard deviation. Learning goal achievement mean and median are approximately homogeneous at a score of two, with standard deviation of 1.08. In terms of physical activity, we might notice that it has a significantly wider range compared to other measurements (for instance, the scale of positive and negative effect is between 1 and 7): a range from 0 to 3960. This is because it was measured through Godin Leisure-Time Exercise Questionnaire, which is calculated by including certain weights of students' daily exercise minutes: mild, moderate and strenuous level. These weights were converted into metabolic equivalents and then based on the sum, a daily leisure activity score was computed [14]. The mean and median vary widely with a large standard deviation. Note that 62 participants reported their age and semester, and 72 subjects reported sleep quality, physical activity, positive affect, negative affect and learning goal achievement.

4.2 Consistency in the original paper

We first check the consistency of the original results and observe if we can reach a similar conclusion. In general, the parameters and significance are alike between the original analysis and the reproduction using Stata in terms of sleep quality. However, we find some inconsistencies in the physical activity variable.

As mentioned in figure 2, when comparing the results from original paper results and Stata output, highlighted cells are the incongruous outcomes.

Total effect: As students increase their average physical activity level, they are more likely to have higher average learning goal achievement ($\hat{\beta} = 0.27$, SE = 0.11, $p = 0.013$). In terms of within-person level (daily effect), on days that students have more strenuous physical activity level, they report lower learning goal achievement ($\hat{\beta} = -0.05$, SE = 0.03, $p = 0.039$). The original study found these results insignificant.

Indirect effect: The mediation effects for negative affect on physical activity and learning goal achievement on between-subject level appear to be significant ($p = 0.032$), and 43% of physical activity on learning goal achievement is mediated by negative affect. These conclusions are different than the reported results, although a marginal significant level of indirect effect ($p = 0.051$) and a very close mediation proportion were found in the original study.

Physical activity Positive affect on between-subject level

	Original Output		Stata Output	
	B (SE)	p	B (SE)	p
a (phyact ->PA)	0.87 (0.17)	<0.001	0.81 (0.20)	<0.001
b (PA->LGA)	0.30 (0.05)	<0.001	0.30 (0.06)	<0.001
ab (indirect effect)	0.27 (0.07)	<0.001	0.25 (0.07)	0.001
Mediated proportion (%)	88%		90%	
c (total effect)	0.30 (0.17)	0.079	0.27 (0.11)	0.013
c' (direct effect)	0.04 (0.18)	0.839	0.03 (0.10)	0.791

Physical activity Negative affect on between-subject level

	Original Output		Stata Output	
	B (SE)	p	B (SE)	p
a (phyact ->NA)	-0.19 (0.07)	0.007	-0.18 (0.07)	0.009
b (NA->LGA)	-0.66 (0.19)	0.001	-0.67 (0.18)	<0.001
ab (indirect effect)	0.13 (0.07)	0.051	0.12 (0.05)	0.032
Mediated proportion (%)	42%		43%	
c (total effect)	0.30 (0.17)	0.081	0.27 (0.11)	0.014
c' (direct effect)	0.17 (0.18)	0.346	0.15 (0.10)	0.143

Physical activity Positive affect on within-subject level

	Original Output		Stata Output	
	B (SE)	p	B (SE)	p
a (phyact ->PA)	0.17 (0.04)	<0.001	0.17 (0.03)	<0.001
b (PA->LGA)	0.17 (0.03)	<0.001	0.17 (0.02)	<0.001
ab (indirect effect)	0.03 (0.01)	<0.001	0.03 (0.01)	<0.001
Mediated proportion (%)	27%		26%	
c (total effect)	-0.05 (0.03)	0.116	-0.05 (0.02)	0.039
c' (direct effect)	-0.08 (0.03)	0.010	-0.08 (0.02)	0.001

Physical activity Negative affect on within-subject level

	Original Output		Stata Output	
	B (SE)	p	B (SE)	p
a (phyact ->NA)	-0.05 (0.01)	0.001	-0.05 (0.01)	<0.001
b (NA->LGA)	-0.48 (0.07)	<0.001	-0.48 (0.05)	<0.001
ab (indirect effect)	0.02 (0.01)	0.001	0.02 (0.01)	<0.001
Mediated proportion (%)	23%		24%	
c (total effect)	-0.05 (0.03)	0.117	-0.05 (0.02)	0.046
c' (direct effect)	-0.07 (0.03)	0.015	-0.07 (0.02)	0.003

Figure 2: Results Consistency Check

4.3 Mixed-effects location scale model

4.3.1 Mediation model MixWILD output (outcome: negative affect)

Due to a large range of scale in physical activity, the authors took the square root of physical activity (SqrtPhysAct) and then divided by 10. We followed their transformation. Output from table 4 demonstrates mediation model output: the association between physical activity and negative affect.

Variable	Estimate	SE	p-value
BETA (regression coefficients)			
Intercept	3.295	0.275	<0.001
Week	0.071	0.028	0.010
Week^2	-0.009	0.008	0.276
Week^3	-0.021	0.007	0.005
SqrtPhysAct_BS	-0.409	0.168	0.015
SqrtPhysAct_WS	-0.017	0.014	0.203
ALPHA (BS variance parameters: log-linear model)			
Intercept	-0.202	0.175	0.249
Week	0.039	0.028	0.167
TAU (WS variance parameters: log-linear model)			
Intercept	0.432	0.333	0.194
Week	0.067	0.028	0.018
SqrtPhysAct_BS	-0.378	0.204	0.063
SqrtPhysAct_WS	-0.019	0.040	0.639
Random scale standard deviation			
Std Dev	0.876	0.083	<0.001
Random location (mean) effect on WS variance			
Loc Eff	0.635	0.123	<0.001

Table 4: Mediation Model Output (n = 72 subjects, $\sum n_i = 2108$ observations)

Variable	Ratio	Lower CI	Upper CI
ALPHA (BS variance parameters: log-linear model)			
Intercept	0.817	0.580	1.152
Week	1.039	0.984	1.098
TAU (WS variance parameters: log-linear model)			
Intercept	1.541	0.803	2.957
Week	1.069	1.012	1.129
SqrtPhysAct_BS	0.685	0.460	1.021
SqrtPhysAct_WS	0.981	0.907	1.062
Random location (mean) effect on WS variance			
Location Effect	1.887	1.482	2.402
Random scale standard deviation			
Std Dev	2.402	2.043	2.825

Table 5: BS and WS Variance Ratios and 95% CIs (Mediation Model)

- Mean model: The **intercept** (negative affect) is estimated to be 3.3. This represents the estimates when week is zero (i.e. on about day 16) and physical activity on BS and WS level is zero. However, this estimate may not be relevant since, because all students participated in some degree of physical activity during the study, BS level of physical activity never goes to zero. The slope for time variable **week** is slightly positive and significant ($\hat{\beta} = 0.07, p = 0.01$). However, the slope for **week**^{2} and **week**^{3} are both negative, and the quadratic term is insignificant and cubic term is significant, which shows both a linear and cubic trend of negative affect as time passes. After purely using time-related variables and intercept, negative affect does not change much, staying at around 3.2 to 3.3. The slope for **SqrtPhysAct_BS** is -0.41 and significant at $p = 0.015$ and **SqrtPhysAct_WS** is -0.02 but insignificant. This represents that active average physical activity results in lower negative affect, but not on a daily level.

- BS variance model: As mentioned before, MixWILD program provides the exponential statistics from table 5. The effect of **week** estimate is positive but not significant ($\hat{\alpha} = 0.04$, $p = 0.17$). The exponential slope reflects a variance ratio, which implies ratio of BS variance comparing value one week apart. Ratio of 1.04 represents that BS variance increased by a factor of 4% per week.

Conclusion: there is no evidence that subjects become more heterogeneous in negative affects over time.

- WS variance model: Similar to BS variance model, the program provides the exponential statistics for WS variance submodel. Only the predictor **week** is significant at $p = 0.018$ ($\hat{\tau} = 0.067$). Table 5 indicates the corresponding exponential slope is 1.07 with a 95% confidence interval from 1.01 to 1.13. The exponential slope represented a variance ratio, which implies the ratio of WS variance comparing value one week apart. Ratio of 1.07 reflects that WS variance increased by a factor of 7% per week. This reflects that subjects are less consistent over time in terms of negative affect. The intercept and the physical activity variables are insignificant.

- Errors that were not captured by covariates in WS variance model were left in the standard deviation of random scale. The estimate here is 0.88 and highly significant. Hence, the variation between each subject still varies substantially after taking into account existing covariates. The association between random location and scale effect is positive and significant ($\hat{\tau} = 0.64$, $p < 0.001$), which indicates that subjects with higher average negative affect are also less consistent, and subjects with lower average negative affect are more consistent.

4.3.2 Full model MixWILD output (outcome: learning goal achievement)

Variable	Estimate	SE	p-value
BETA (regression coefficients)			
Intercept	2.587	0.281	<0.001
Week	−0.106	0.036	0.003
Week^2	−0.033	0.013	0.011
Week^3	0.033	0.011	0.004
NA_BS	−0.246	0.069	<0.001
NA_WS	−0.172	0.018	<0.001
SqrtPhysAct_BS	0.183	0.105	0.080
SqrtPhysAct_WS	−0.071	0.024	0.003
ALPHA (BS variance parameters: log-linear model)			
Intercept	−1.246	0.182	<0.001
Week	0.112	0.055	0.042
TAU (WS variance parameters: log-linear model)			
Intercept	−0.275	0.257	0.285
Week	−0.085	0.027	0.002
NA_BS	−0.011	0.063	0.862
NA_WS	0.066	0.030	0.030
SqrtPhysAct_BS	−0.046	0.097	0.635
SqrtPhysAct_WS	0.035	0.042	0.409
Random scale standard deviation			
Std Dev	0.410	0.049	<0.001
Random location (mean) effect on WS variance			
Loc Eff	−0.066	0.064	0.299

Table 6: Full Model Output (n = 72 subjects, $\sum n_i = 2046$ observations)

Variable	Ratio	Lower CI	Upper CI
ALPHA (BS variance parameters: log-linear model)			
Intercept	0.288	0.201	0.411
Week	1.119	1.004	1.246
TAU (WS variance parameters: log-linear model)			
Intercept	0.760	0.459	1.257
Week	0.918	0.871	0.968
NA_BS	0.989	0.874	1.119
NA_WS	1.068	1.006	1.133
SqrtPhysAct_BS	0.955	0.791	1.154
SqrtPhysAct_WS	1.035	0.954	1.124
Random location (mean) effect on WS variance			
Location Effect	0.936	0.826	1.060
Random scale standard deviation			
Std Dev	1.507	1.369	1.659

Table 7: BS and WS Variance Ratios and 95% CIs (full model)

- Mean model:

  1. Time-related variables are all significant. After purely considering time-related variables and intercept, it is discovered that learning goal achievement changes from 2.2 to 2.5 from week 0 to the end of study without much change.
  2. **NA_BS** and **NA_WS** effects are both negative and significant ($\hat{\beta} = -0.25$, $p < 0.001$ and $\hat{\beta} = -0.17$, $p < 0.001$ respectively). This represents that higher negative affect results in lower learning goal achievement based on average level across time and daily basis.
  3. **SqrtPhysAct_BS** is positive but insignificant ($\hat{\beta} = 0.18$ and $p = 0.08$) while **SqrtPhysAct_WS** is negative and significant ($\hat{\beta} = -0.07$ and $p = 0.003$). This represents that there is no statistical evidence to show that active average physical activity is related to better learning goal achievement outcomes, whereas on a day-to-day level, higher physical activity level is associated with lower learning goal achievement.

- BS variance model: Table 7 provides the exponential estimates from MixWILD.

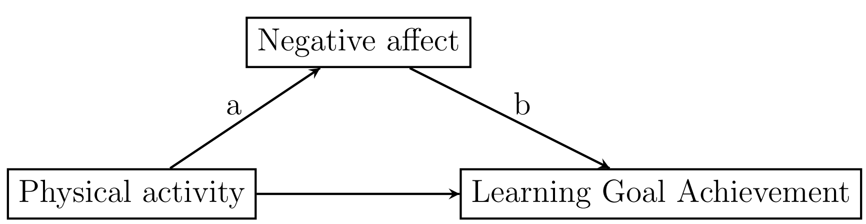
The BS variance intercept is significant and estimates is 0.29 with a 95% confidence interval of 0.20 to 0.41. The facts that covariate **week** is significant ($p = 0.042$) and its exponential slope is 1.12 shows that a BS variance increases by a factor of 12% per week. Therefore, there are greater discrepancies over time between individuals in learning goal achievement levels.

- In terms of WS variance model, only **week** and **NA_WS** effects are significant.

  1. The exponential slope for **week** is 0.92 with a 95% confidence interval from 0.87 to 0.97. This means WS variance reduces by a factor of 8% per week, which shows that subjects become less erratic (more stable) in learning goal achievement as time goes on.
  2. Regarding **NA_WS**, an exponential slope estimate of 1.07 with a 95% confidence interval of 1.01 to 1.13 shows that WS variance in learning goal achievement increases by a factor of 7% for one unit change in negative affect. On days that students have higher negative affect, they also appear to be more erratic in learning goal achievement.
  3. Both between subject and within subject levels on physical activity are not significant (**SqrtPhysAct_BS**: $\hat{\tau} = -0.05, p = 0.63$ and **SqrtPhysAct_WS**: $\hat{\tau} = 0.03, p = 0.41$). No significant evidence is found for consistency in learning goal achievement using physical activity as a predictor. This is true whether we consider the average physical activity over the 32-day examination period or just the physical activity on any given day.

- As for standard deviation of random scale, the estimate is 0.41 and highly significant. Hence, subjects vary substantially with regards to how consistent or erratic they are in learning goal achievement after considering existing covariates. The relationship between the random location and scale effect turns out to be negative but not significant ($\hat{\tau} = -0.066, p = 0.299$).

4.3.3 Summary of the model



Path	Estimators	SE	P-value
a: PhysAct_WS → NA	−0.017	0.014	0.203
b: NA_WS → LGA	0.066	0.030	0.030
ab (indirect effect)	−0.001	0.001	0.272
Mediated proportion (%)	3%		
c (total effect)	0.021	0.042	0.610
PhysAct → LGA (direct effect)	0.035	0.042	0.409

Table 8: Summary statistics table

Based on the section 4.3.1 mediation model output and 4.3.2 full model output, a summarized table 8 is shown. Path a and path b indicate that on a daily basis, higher levels of students exercise are correlated with lower negative affect (but not significant), and furthermore, lower negative affect is associated with a more consistent learning goal achievement ($\hat{\tau} = 0.066$, SE $= 0.030$, $p = 0.030$).

Indirect effect and direct effect: Indirect effect is the product of path a and b. Standard error and p-value are calculated using the Sobel test [30]. Sobel test is used to examine if there is a mediation effect between predictors and response variable. A detailed computation and example can be found in this short article [39]. Non-significant level of indirect effect implies that negative affect is not a mediator between physical activity and learning goal achievement. A low 3% of mediated proportion also confirms the results. Note here the mediation proportion is calculated by mediation (indirect effect) over the sum of individual absolute values of both indirect and direct effect [3]. After we take into account the mediation effect, p-value in direct effect also shows not significant.

Total effect: Note that mediation and full model MixWILD output tables above do not provide total effect estimates; what we suggest is, when fitting the model, to only include week, week^2, week^3, within-subject level of physical activity as covariates and learning goal achievement as an outcome variable in MixWILD as a new model to get the total effect. Insignificant total effect indicates that daily level of physical activity is not statistically associated with consistency level of learning goal achievement.

5 Discussion

The fact that the results are different compared to the original paper indicates that there may be some unexplained details in the original study. We find that physical activity predicts learning goal achievement over time and on a daily basis. Reuter and Forster also supported these findings since they concluded that higher level of physical activity leads to better grade point average among 600 undergraduates in a US state university [31]. In addition, negative affect is determined to be a mediator between physical activity and learning goal achievement. Despite it being hard to find literature that shows negative affect as a mediator for physical activity and learning goal achievement specifically, existing studies discovered that any degree of physical activity assists in lowering depression level [26], and students experiencing more emotional difficulties are more likely to encounter higher negative affect and poor performance in academic [24].

Besides the original paper, there are several novel findings. In the mediation model, a ratio of 1.07 in week reflects that WS variance in negative affect increases by a factor of 7% per week, which implies that subjects are less consistent in negative affect over time. Another estimate worth noticing is the positive and significant relationship between the random location and scale effect, indicating subjects with higher average negative affect level fluctuate more in their mood, and subject with lower average negative affect level vary less in their mood. In the full model, significant levels of week in the BS variance and WS variance demonstrate that subjects become more heterogeneous and less erratic (more consistent) in learning goal achievement as time goes on.

In our mixed-effects location scale model summary, our analysis does not provide us with many significant outcomes. We only obtain the results that, on days that students experience higher level of negative affect results in a less stable learning goal achievement. Current literature has not investigated many studies in these aspects; however, a longitudinal cohort study did reveal negative affect indeed is associated with poor academic studies [36].

5.1 Limitations

In this study, certain limitations should be mentioned. First, this dataset had relatively small sample size. After excluding the students who dropped out or did not provide the final exam grades, only 72 subjects were included, which to a large extent decrease the likelihood of obtaining significant results. Second, studies were done in Switzerland, so it maybe hard to generalize to students in other countries, especially because the education system is different in European countries than in the United States and other countries in the world. Last but not least, these models assume normally distributed outcomes and random effects. The precision of the model might be affected due to the violations of normality. It is possible to empirically test this using the Liu approach for non-normal random effects models [23].

6 Conclusions

The EMA data collection method provides opportunities for researchers to model subjects' variance: how subject levels differ compared to others (between-subject variability) and how each subject varies over time (within-subject variability). It can also minimize the subjects' recall memory bias. Our findings provide additional evidence that more active physical activity yields higher learning goal achievement across several days, while active daily exercise level leads to lower daily learning goal achievement. Moreover, a new finding is that daily higher level of negative affect is related to more erratic learning goal achievement. This study provides some insights on the relationship between health behaviors such as sleep and physical activity and academic performance via mood affect using mixed-effects location scale model, which assists schools to raise awareness about their students' physical and mental health. Future studies on a larger sample size should be considered to explore and detect if the conclusions are robust.

References

[1] Aimé, A., Villatte, A., Cyr, C., Marcotte, D. (2017). Can weight predict academic performance in college students? An analysis of college women's self-efficacy, absenteeism, and depressive symptoms as mediators. *Journal of American College Health, 65*(3), 168-176. https://doi.org/10.1080/07448481.2016.1266639

[2] Alhazmi, A., Aziz, F., Hawash, M. M. (2021). Association of BMI, Physical Activity with Academic Performance among Female Students of Health Colleges of King Khalid University, Saudi Arabia. *International journal of environmental research and public health, 18*(20). https://doi.org/10.3390/ijerph182010912

[3] Alwin, D. F., Hauser, R. M. (1975). The Decomposition of Effects in Path Analysis. *American Sociological Review, 40*(1), 37–47.

[4] Baron, R. M., Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

[5] Barta, A., Tamás, B., Szamosközi, I. (2019). Human mediators of the relationship between metacognitive awareness and academic achievement: parents' and teachers' support. A mediation analysis. *Transylvanian Journal of Psychology,* 2, 84–102.

[6] Courtney, J. B., Lipsey, T., Braun, B., Henry, K., Nelson, T. L., Li, K. (2020). Using Ecological Momentary Assessment to Examine the Effects of Duty Status on Acute Stress and Tiredness in Firefighters: A Pilot Study. *Journal of Occupational and Environmental Medicine, 62*(10), 859-870. https://doi.org/10.1097/JOM.0000000000001988

[7] De Vries, L. P., Baselmans, B. M., Bartels, M. (2021). Smartphone-based ecological momentary assessment of well-being: A systematic review and recommendations for future studies. *Journal of Happiness Studies, 22*(5), 2361-2408. https://doi.org/10.1007/s10902-020-00324-7

[8] Desirée Colombo, Azucena Garcia Palacios, Javier Fernandez Alvarez, Andrea Patané, Michelle Semonella, Pietro Cipresso, Marta Kwiatkowska, Giuseppe

Riva, Cristina Botella. (2018). Current state and future directions of technology-based ecological momentary assessments and interventions for major depressive disorder: protocol for a systematic review. *Systematic Reviews, 7*(1), 1–7. https://doi.org/10.1186/s13643-018-0899-y

[9] Dewald, J. F., Meijer, A. M., Oort, F. J., Kerkhof, G. A., Bögels, S. M. (2010). The influence of sleep quality, sleep duration and sleepiness on school performance in children and adolescents: A meta-analytic review. *Sleep Medicine Reviews, 14*(3), 179–189. https://doi.org/10.1016/j.smrv.2009.10.004

[10] Dunton, G. F. (2017). Ecological momentary assessment in physical activity research. *Exercise and sport sciences reviews, 45*(1), 48–54. https://doi.org/10.1249/JES.0000000000000092

[11] Dzubur, E., Ponnada, A., Nordgren, R., Yang, C. H., Intille, S., Dunton, G., Hedeker, D. (2020). MixWILD: A program for examining the effects of variance and slope of time-varying variables in intensive longitudinal data. *Behavior research methods, 52*(4), 1403-1427. https://doi.org/10.3758/s13428-019-01322-1

[12] Ebner-Priemer, U. W., Trull, T. J. (2009). Ecological Momentary Assessment of Mood Disorders and Mood Dysregulation. *PSYCHOLOGICAL ASSESSMENT, 21*(4), 463–475.

[13] Fletcher, J. (2016). Applying self-determination theory to college students' physical-activity behavior: Understanding the motivators for physical (in) activity. *Communication Studies, 67*(5), 489-508. https://doi.org/10.1080/10510974.2016.1212911

[14] Flueckiger, L., Lieb, R., Meyer, A. H., Mata, J. (2014). How health behaviors relate to academic performance via affect: An intensive longitudinal study. *PLoS One, 9*(10), https://doi.org/10.1371/journal.pone.0111080

[15] Hayley, A. C., Sivertsen, B., Hysing, M., Vedaa, Ø., Øverland, S. (2017). Sleep difficulties and academic performance in Norwegian higher education students. *British Journal of Educational Psychology, 87*(4), 722-737. https://doi.org/10.1111/bjep.12180

[16] Hedeker, D., Gibbons, R. D. (2006). *Longitudinal data analysis.* Wiley-Interscience.

[17] Hedeker, D. Mermelstein, R.J. (2022). Modeling Variation in Intensive Longitudinal Data. In A.A. O'Connell, D. B. McCoach, B. Bell (Eds.), Multilevel Modeling Methods with Introductory and Advanced Applications. *Information Age Publishing.*

[18] Hedeker, D., Mermelstein, R. J., Berbaum, M. L., Campbell, R. T. (2009). Modeling mood variation associated with smoking: An application of a heterogeneous mixed-effects model for analysis of ecological momentary assessment (EMA) data. *Addiction, 104*(2), 297-307. https://doi.org/10.1111/j.1360-0443.2008.02435.x

[19] Hedeker, D., Mermelstein, R. J., Demirtas, H. (2008). An application of a mixed-effects location scale model for analysis of ecological momentary assessment (EMA) data. *Biometrics, 64*(2), 627-634. https://doi.org/10.1111/j.1541-0420.2007.00924.x

[20] Hedeker, D., Mermelstein, R. J., Demirtas, H. (2012). Modeling between-subject and within-subject variances in ecological momentary assessment data using mixed-effects location scale models. *Statistics in medicine, 31*(27), 3328-3336. https://doi.org/10.1002/sim.5338

[21] Kim, B. (2016, April 18). *Introduction to Mediation Analysis.* University of Virginia Library Research Data Service + Science. https://data.library.virginia.edu/introduction-to-mediation-analysis/

[22] Kracht, C. L., Beyl, R. A., Maher, J. P., Katzmarzyk, P. T., Staiano, A. E. (2021). Adolescents' sedentary time, affect, and contextual factors: An ecological momentary assessment study. *International Journal of Behavioral Nutrition and Physical Activity, 18*(1). https://doi.org/10.1186/s12966-021-01121-y

[23] Liu, L., Yu, Z. (2008). A likelihood reformulation method in non-normal random effects models. *Statistics in medicine, 27*(16), 3105-3124.

[24] Mª de los Ángeles Sánchez-García, Beatriz Lucas-Molina, Eduardo Fonseca-Pedrero, Alicia Pérez-Albéniz, Mercedes Paino. (2018). Emotional and behavioral difficulties in adolescence: relationship with emotional well-being, affect, and academic performance. *Anales de Psicología, 34*(3), 482–489. https://doi.org/10.6018/analesps.34.3.296631

[25] MacKinnon, D. P., Fairchild, A. J., Fritz, M. S. (2007). Mediation analysis. *Annual review of psychology, 58,* 593–614. https://doi.org/10.1146/annurev.psych.58.110405.085542

[26] Mammen, G., Faulkner, G. (2013). Physical Activity and the Prevention of Depression: A Systematic Review of Prospective Studies. *American Journal of Preventive Medicine, 45*(5), 649–657. https://doi.org/10.1016/j.amepre.2013.08.001

[27] Noman, M., Kaur, A., Nafees, N. (2021). Covid-19 fallout: Interplay between stressors and support on academic functioning of Malaysian university students. *Children and Youth Services Review, 125.* https://doi.org/10.1016/j.childyouth.2021.106001

[28] O'Hare, K., White, N., Harding, R., Galland, B., Sellbom, M., Shine, B., Schaughency, E. (2021). Sluggish cognitive tempo and daytime sleepiness mediate relationships between sleep and academic performance. *Journal of Developmental Behavioral Pediatrics, 42*(8), 637-647. https://doi.org/10.1097/DBP.0000000000000948

[29] Piro, R. S., Alhakem, S. S. M., Azzez, S. S., Abdulah, D. M. (2018). Prevalence of sleep disorders and their impact on academic performance in medical students/University of Duhok. *Sleep and Biological Rhythms, 16*(1), 125-132.

[30] Preacher, K. J., Leonardelli, G. J. (2001, March). *Calculation for the Sobel test: An interactive calculation tool for mediation tests.* Quantpsy.Org. Retrieved May 3, 2022, from http://www.quantpsy.org/sobel/sobel.htm

[31] Reuter, P. R., Forster, B. L. (2021). Student health behavior and academic performance. *PEERJ, 9*, e11107. https://doi.org/10.7717/peerj.11107

[32] Richardson, M., Abraham, C., Bond, R. (2012). Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological bulletin, 138*(2), 353–387.

[33] Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., Carlstrom, A. (2004). Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis. *Psychological Bulletin, 130*(2), 261–288. https://doi.org/10.1037/0033-2909.130.2.261

[34] Rogaten, J., Moneta, G. B. (2017). Positive and negative structures and processes underlying academic performance: a chained mediation model. *Journal of Happiness Studies, 18*(4), 1095-1119. https://doi.org/10.1007/s10902-016-9765-6

[35] Solberg, R. B., Steene-Johannessen, J., Anderssen, S. A., Ekelund, U., Säfvenbom, R., Haugen, T., Berntsen, S., Åvitsland, A., Lerum, Ø., Resaland, G. K., Kolle, E. (2021). Effects of a school-based physical activity intervention on academic performance in 14-year old adolescents: a cluster randomized controlled trial – the School in Motion study. *BMC Public Health, 21*(1). https://doi.org/10.1186/s12889-021-10901-x

[36] Suheir Awadalla, E. Bethan Davies, Cris Glazebrook. (2020). A longitudinal cohort study to explore the relationship between depression, anxiety and academic performance among Emirati university students. *BMC Psychiatry, 20*(1), 1–10. https://doi.org/10.1186/s12888-020-02854-z

[37] Sulla, F., Aquino, A., Rollo, D. (2022). University Students' Online Learning During COVID-19: The Role of Grit in Academic Performance. *Frontiers in Psychology, 13*, https://doi.org/10.3389/fpsyg.2022.825047

[38] Von der Embse, N. P., Schultz, B. K., Draughn, J. D. (2015). Readying students to test: The influence of fear and efficacy appeals on anxiety and test performance. *School Psychology International, 36*(6), 620-637. https://doi.org/10.1177/0143034315609094

[39] Yay, M.(2017). The Mediation Analysis With the Sobel Test and the Percentile Bootstrap. *International Journal of Management and Applied Science, 3*(2), 129-131