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Effect of Different Learning Methods on Students' Performances in Statistics

Nurain Huzaifah Yusniman [a], Zarina Mohd. Khalid [b]*
[a,b]Department of Mathematical Sciences, Faculty of Science, Universiti Teknologi Malaysia,
81310 Johor Bahru, Johor, Malaysia.
*Corresponding author: zarinamkhalid@utm.my

Abstract
This research focuses on application of nonparametric methods to compare the students' performances from learning face-to-face and online. Shapiro-Wilk test analyzed that the data violated normality assumption. Statistical analysis of Mann-Whitney U Test and Kruskal Wallis Test were conducted to study whether differences of the scores are significant against their learning methods and sections, and the necessity to implement objective assessment. M-estimation is also utilized to estimate the parameters of interaction term between the two variables.
It is found that online learning indicated improved outcomes against physical learning and there is no necessity to conduct objective evaluation in the assessment.
Keywords: Nonparametric methods; students' performances; face-to-face; online; Mann-Whitney U Test; Kruskal Wallis Test; objective assessment; M-estimation; robust regression

1 Introduction

Wuhan, a developing business centre of China has witnessed an outbreak of a new coronavirus at the end of 2019 [1] which has been identified by Chinese researchers as the novel Coronavirus Disease [2], also known as COVID-19. Within months, the virus spread fast across the world, became a global health threat and affected developing countries including Malaysia.

Therefore, Malaysian government with advice from Ministry of Health (MoH) has immediately taken serious measures to prevent the pandemic from spreading out. Given the rapid increase of the local cases in short time, the national MCO was then announced on 18th of March 2020 to control the disease [3]. Due to that, colleges, universities, and other higher educational institutions all over the country closed their campuses immediately and had to undergo sudden transition from face-to-face to online delivery mode and thus gave rise to worrying queries on the quality of education [1].

Online learning has now emerged as a modern way of learning in developed countries, as it is also seen as the only option to replace traditional teaching in all types of academic institutions [4]. Prior to the pandemic, students were able to interact directly with lecturers during classes, exams, and even when they required personal consultation. Aside from that, active learning activities such as brainstorming and volunteering can be easily carried out during classes. During online learning, all interactions between lecturers and students are conducted in real time using a variety of online tools such as Webex, Zoom, Google Meet, and others. In some cases, pre-recorded lecture videos are prepared for students to watch at their own preferred time [5].

The objective of this research is to compare the students' performances between different learning environments by applying nonparametric methods to analyse abnormal data. From the comparison, it is possible to identify whether the different learning environment hold significant impact on students' performances. Other than that, this study also aims to determine the needs to incorporate objective assessment as a part of the students' evaluation.

2 Literature Review

2.1 Online Distance Learning versus Face-to-Face Comparative Studies.

A lot of similar studies investigating the difference between two different learning environments have been conducted many years ago.

Some studies supported the notion that online learning performs at least equal to or better than in-class learning. Navarro and Shoemaker [6] studied a matched pair of distinct instructional modes for a macroeconomics course and reported no significant difference between the results. A survey by Brown and Liedholm [7] was conducted in which a matched pair of online and in-class formats was set up for an economics course taught by the same instructor. Their final exam scores showed that the online mode scores were 6% higher than those from physical learning. A. Jensen [8] conducted the similar study in an introduction psychology course and indicated that these two modes have similar learning outcomes, but the students picked in-class mode to their favour.

To date, similar studies had been initiated by many in which the difference is explored through various views, mainly by collecting responses from the students. They recorded that there is an increased positivity among them about online learning during the pandemic according to a feedback from Centre of Pre-University Studies (PPPU), Universiti Malaysia Sarawak (UNIMAS), Malaysia [9]. According to the findings of study by Kaur et al. [10], online classes were also similarly effective in five out of ten dimensions and less effective in the remaining, but the students reviewed that distance-learning was not equivalent to traditional classroom instruction in any way. In another study, students state about their struggle to adapt with the new environment hence not being able to score well for their examination [11]. They even opt for physical learning if the pandemic subsides in the future.

2.2 Influence of Technology in Teaching

Digital technologies have been integrated into schooling throughout the previous few decades, affecting the context of teaching and learning through access to computers, the internet, online learning platforms, and communication tools. As a result, various levels of digital technology integration into educational systems have emerged [10].

The technologies used at home for learning ranged from basic to advanced. Students continued their schooling in low-tech homes by watching national education tv broadcasts or using texts or worksheets. Mid-tech homes had unreliable Internet, shared machines, or just cell phones to view materials and communicate with their teacher and other pupils, whereas high-tech homes had fast connectivity and access to immersive learning opportunities via computers [12]. The minimum technical requirements for effective distance learning are the acquisition of hardware such as a monitor, mobile phone (cellular phones), or camera, video conferencing software such as WebEx, Zoom, or Microsoft Teams, Microsoft Windows or Apple operating systems, and a secure internet network [13].

In Finland, the school days consisted of 2–4 live lessons every day via Google Meet, followed by 40–50 minutes of independent work before the class reconvened for another live session with a 15-minutes break between them. Most of the time, the assignments were given to the students the night before and reviewed by the teachers in Google at the end of the school day. Quite similar scenario also take place in India. One of the public schools' special instructors used WhatsApp to contact with their students frequently. Every two weeks, a 15-day lesson plan alongside brief assignments and activities is sent to their parents or caregivers. There are also weekly online meetings for most of the student-parent pairs who are associated with the educators to check on results, have brief interventions, and address any problems. Through these two scenarios, despite the environmental conditions or limitation in technology advancement, educators, students and parents are still putting effort to adapt to this new kind of learning mode by fully making use of the technology system.

2.3 Nonparametric Methods

2.3.1 Mann-Whitney Test

Mann-Whitney test, figured out by Mann and Whitney in 1947 is one of the most commonly used non-parametric statistical tests. The function of this test is to compare differences between two independent groups when the distribution of the dependent variable is not normal [14]. The independent t-test, on the other hand, is used to compare the means of two independent groups and requires samples to meet certain assumptions such as normality, equal variances, and independence. It is a parametric test that requires samples to satisfy certain assumptions such as normality, equal variances, and independence. Hence, the Mann-Whitney Test, which can be referred as the nonparametric approach of t-test, are more appropriate and preferable to be used when assumptions of the parametric method are violated [15].

2.3.2 Kruskal-Wallis Test

Named after William Kruskal and W. Allen Wallis, this test which is an extension of the Mann–Whitney test is considered as the nonparametric alternative to the one-way ANOVA, as unlike parametric ANOVA, it does not require the normal distribution, interval data, or homogeneity of group variance assumptions to be fulfilled [16]. Despite the fact that both the Kruskal-Wallis test and one-way ANOVA aim to see if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable, the nonparametric approach, which relies on variation among ranked sample means, is more compact, convenient, easy to use, and efficient than its parametric counterpart [16].

2.3.3 M-estimator

In cases such as the existence of outliers, the classical method of parameter estimation which is Least Square (LS) method has shown poor performance to cater to the problem, according to Bellio and Ventura [17]. Hence, initiatives in the literature to develop statistical approaches that are resistant to violation of assumptions on regression analysis were initiated and have been ongoing since 1960s. The robustness theory was first introduced by Huber and Hampel which further played a significant contribution in the development of robust regression analysis. For example, in the context of an M-estimator, Godambe in 1960 has established the concept of an optimum estimating function, and his article is regarded as a precursor of the M-estimator methodology. Liang and Zeger popularised M-estimators in the biostatistics field two decades later under the appellation generalised estimating equations (GEE) [18].

The main goal of robust regression analysis is to find a model that accurately represents the majority of the data around the mean [19] when fundamental assumptions are not met. There are indeed various classes of robust estimators such as S-estimators and MM-estimators which are the extensions of M-estimation [19]. The performance of M-estimators is nearly identical to that of the least squares approach, according to the study [20] and this is due to their essential mathematical structure, which makes them less sensitive to misleading violation Menezes et al., [21]. In this study, this technique acts as a nonparametric alternative to Two-Way ANOVA.

3 Formulation of Test Statistics

3.1 Mann-Whitney Test

Suppose there is a sample of n_x observations $\{x_1, x_2, \dots, x_n\}$ in a group and a sample of n_y observations $\{y_1, y_2, \dots, y_n\}$ in a group in which both come from different population. The basic idea of the Mann-Whitney test is about comparing every observation x_i in first sample with every observation y_j in second sample. So, the total pairs that can be formed are $n_x n_y$ which yields the maximum number of possible paired comparisons [13].

The test statistic for the Mann-Whitney test, denoted as U is defined as follows:

$$U_x = n_x n_y + \left(\frac{n_x(n_x+1)}{2}\right) - R_x \ , if \ \ n_x > n_y \tag{1}$$

$$U_y = n_x n_y + (\frac{n_y(n_y+1)}{2}) - R_y \ \ , if \ \ n_y > n_x \tag{2}$$

where n_x is the number of observations in the first group, n_y is the number of observations in the second group, R_x is the sum of the ranks assigned to the first group and R_y for the other. The final value for U-statistic is the lower value of U between U_x and U_y. If both samples have equal medians, then each of x_i has an equal chance to be greater or smaller than y_j. Thus, the hypothesis are written as:

$$H_0 : P(x_i > y_j) = \frac{1}{2} \tag{3}$$

$$H_1 : P(x_i > y_j) \neq \frac{1}{2} \tag{4}$$

If the two medians of the groups are different, the null hypothesis is rejected. They are then suggested as coming from two different populations.

3.2 Kruskal-Wallis Test

Conceptually similar with Mann-Whitney U Test, in this test, any of N observations is replaced by a rank in relation to all of the other observations across all samples. By dividing the total of ranks of each observation by n, the number of observations in each category is determined by the mean of the ranks [20].

The test statistic for the Kruskal-Wallis test, denoted as H is defined as follows:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{n} \frac{T_i^2}{N_i} - 3(N+1) \tag{5}$$

where N is the sum of sample sizes for all samples, T_i is the sum of ranks in i^{th} sample and N_i is the size of i^{th} sample. The hypotheses for the test are:

H_0: population medians are equal
H_1: population medians are not equal

3.3 M-estimator

M-estimator is an extension of the maximum likelihood estimation which works by replacing the squared residuals in OLS, e_i^2 with another function of the residuals that aims to minimize $\sum_{i=1}^{n} \rho(e_i)$ where ρ is a symmetric residual function. The objective can be interpreted as below:

$$\hat{\beta}_M = \min_{\beta} \sum_{i=1}^{n} \rho\left(y_i - \sum_{j=0}^{k} x_{ij}\beta_j\right) \tag{6}$$

which is obtained by completing the following procedures:

$$\min_{\beta} \sum_{i=1}^{n} \rho(\mu_i) = \min_{\beta} \sum_{i=1}^{n} \rho(\frac{e_i}{\hat{\sigma}_{MAD}}) = \min_{\beta} \sum_{i=1}^{n} \rho(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{\hat{\sigma}_{MAD}}) \tag{7}$$

where $e_i = y_i - \sum_{j=0}^{k} x_{ij}\beta_j$, while $\hat{\sigma}_{MAD}$ estimates σ by using the popular scale estimator, Median Absolute Deviation (MAD) such that:

$$\hat{\sigma}_{MAD} = \frac{median|e_i - median(e_i)|}{0.6745} \tag{8}$$

where 0.6745 is selected so that $\hat{\sigma}_{MAD}$ will be asymptotically unbiased when observations are large and normally distributed. Let a weighted function, w_i for any function of ρ be defined as:

$$w_i = \frac{\psi(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{\hat{\sigma}_{MAD}})}{y_i - \sum_{j=0}^{k} x_{ij}\beta_j} \tag{9}$$

where ψ is the derivative of ρ and x_{ij} is i-th observation on the j-th independent variable. By substituting Equation (9) into normal equations:

$$\sum_{i=1}^{n} x_{ij} w_i (y_i - \sum_{j=0}^{k} x_{ij}\beta_j) = 0 \tag{10}$$

Equation (10) expressed in matrix notation as the Weighted Least Squares (WLS) equation is as shown below:

$$\boldsymbol{X}\boldsymbol{W_i}\boldsymbol{X}\beta = \boldsymbol{X}\boldsymbol{W_i}\boldsymbol{Y} \tag{11}$$

where $\boldsymbol{W_i}$ is an $n\ x\ n$ diagonal matrix of weights. Rearranging above equation leads to the final form of the robust estimator of β:

$$\hat{\beta}_M = (\boldsymbol{X}\boldsymbol{W_i}\boldsymbol{X})^{-1}\boldsymbol{X}\boldsymbol{W_i}\boldsymbol{Y} \tag{12}$$

In this study, M-estimation is applied instead of its extension, S-estimation and MM-estimation since we aim to incorporate the basic knowledge, concept and application of the robust regression to our analysis.

4 Results and Discussion

4.1 Descriptive Analysis

Data used is the scores of the Engineering Statistics Course that was obtained from a secondary source. They consist of 4 independent groups from engineering schools in which 2 groups are from School of Mechanical Engineering (SKM), divided into SKM1 (62 observations) and SKM2 (58 observations) while the other 2 groups are from School of Electrical Engineering (SKE), also divided into SKE1 (64 observations) and SKE2 (60 observations). An additional independent data from SKM, labelled as SKM3 is also included in our analysis for a different purpose (68 students).

SPSS version 23 is used to help analyse and describe the data. Table 1 below displays the results of the normality tests of all groups. By referring to the Shapiro-Wilk column, apparently the groups from the mid-MCO period (SKE2 and SKM2) recorded quite smaller p-values which are smaller than 0.05, our significance level compared to those from pre-MCO group (SKE1 and SKM1). This indicates that the data is far from normality.

Table 1:Shapiro-Wilk normality test of each group

Section	**Shapiro-Wilk**		
	Statistic	**df**	**Significance values**
SKE1	.970	64	.127
SKM1	.969	62	.118
SKE2	.927	60	.002
SKM2	.921	58	.001

4.2 Mann-Whitney Test

Our first analysis is to study whether the students' scores have any statistically significant difference when compared based on their learning methods. Referring to Table 2 below, we can see that the p-value obtained for this test, quoted next to 'Asymp. Sig. (2-tailed)' column is 0.000 which is less than 0.05, our significance level. Hence, it is concluded that we have significant evidence to reject the null hypothesis that the distribution of the scores is the same in the two groups (pre-MCO and mid-MCO).

Table 2:Test Statistics of Mann-Whitney Test between Scores-Method

Test Statistics[a]

	Score
Mann-Whitney U	2727.000
Wilcoxon W	10728.000
Z	-8.546
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: Method

This is supported by calculation below:

$$U_x = n_x n_y + \left(\frac{n_x(n_x+1)}{2}\right) - R_x \tag{13}$$
$$= 14868 + \frac{126(127)}{2} - 10728$$
$$= 12141$$
$$U_y = n_x n_y + \left(\frac{n_y(n_y+1)}{2}\right) - R_y \tag{14}$$
$$= 14868 + \frac{118(119)}{2} - 19162$$
$$= 2727$$

The test statistic for the Mann-Whitney U Test is the smaller value between U_x and U_y. Hence, from results obtained above, the value of U-statistic is 2727 from Equation (13) which is lower than 12141 from Equation (14). The results thus indicate that the scores scored by the students learning online are indeed higher than the students taking the same course before the MCO, a difference that is statistically significant.

4.2 Kruskal-Wallis Test

Under Section column, we let “Section 1” to denote SKE1, “Section 2” to denote SKM1, “Section 3” to denote SKE2 and “Section 4” to denote SKM2 for our analysis. Here, Kruskal Wallis Test is utilized to study whether the independent variables, the sections represented by the students caused any significant difference on the student’s scores. The test statistic, from Equation (3) is calculated as follows:

$$H = \frac{12}{244(245)}\left(\frac{5728.5^2}{64} + \frac{4999.5^2}{62} + \frac{8804^2}{60} + \frac{10358^2}{58}\right) - 3(245) \tag{15}$$
$$= 79.492$$

Table 4 below showed that there was a statistically significant difference in the students’ scores between the different sections, χ^2 = 79.553, p = 0.000 which is less than 0.05, with a mean rank score of 89.51 for Section 1, 80.64 for Section 2, 146.73 for Section 3, and 178.59 for Section 4. Thus, we reject the null hypothesis and conclude that at least one of the sections comes from different population.

Table 3:Test statistics of Kruskal-Wallis test between scores-section

Test Statistics[a,b]

	Score
Chi-Square	79.553
df	3
Asymp. Sig.	.000

a. Kruskal Wallis Test

b. Grouping Variable: Section

Dunn's pairwise comparison with Bonferroni adjustment is hence applied to further explore which sections are different to each other. Table 4 from SPSS output below detailed the relationship:

Table 4: Dunn's pairwise comparison between sections

Each node shows the sample average rank of Section.

Sample 1-Sam...	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
2-1	8.871	12.573	.706	.480	1.000
2-3	-66.088	12.778	-5.172	.000	.000
2-4	-97.958	12.889	-7.600	.000	.000
1-3	-57.217	12.679	-4.513	.000	.000
1-4	-89.087	12.791	-6.965	.000	.000
3-4	-31.870	12.992	-2.453	.014	.085

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Apparently, there is a very strong evidence ($p < 0.05$) of a difference between SKE1-SKE2 and SKE1-SKM2 which explains the strong impact of contrasting method of learning. The same explanation applies to SKM1-SKE2 and SKM1-SKM2 where the contrary is only proved between those sections coming from different method of learning.

4.3 Kruskal-Wallis Test for Objective Assessment

The scores of the students from SKM1, SKM2 and SKM3 are compared for this follow-up test. Under Assessment column, we let "1" to denote SKM1, which conducts face-to-face learning with no objective evaluation, "2" to denote SKM2, which incorporates objective assessment during online learning and "3" to denote SKM3, where the Teaching and Learning is still being organized virtually but without any objective assessment.

$$H = \frac{12}{188(189)}\left(\frac{53.46774^2}{62} + \frac{126.0862^2}{58} + \frac{104.9706^2}{68} + \right) - 3(189) \qquad (16)$$
$$= 57.3141$$

With total number of observations equal to 188, we are able to compute the H-statistic value as shown in Equation (7). Table 5 below displays the results from SPSS output where apparently, there was a statistically significant difference in the students' scores between the different sections, χ^2 = 57.354. Thus, we reject the null hypothesis and conclude that at least one of the sections comes from different population.

Table 5: Test statistics of Kruskal-Wallis test between scores-assessments

Test Statistics[a,b]

	Scores
Chi-Square	57.354
df	2
Asymp. Sig.	.000

a. Kruskal Wallis Test

b. Grouping Variable: Assessment

We then utilized Dunn's pairwise comparison with Bonferroni adjustment to further study which sections are different to each other. Table 6 from SPPS output below detailed the relationship:

Table 6: Dunn's pairwise comparison between type of assessments

Each node shows the sample average rank of Assessment.

Sample 1-Sam...	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
1-3	-51.503	9.552	-5.392	.000	.000
1-2	-72.618	9.937	-7.308	.000	.000
3-2	21.116	9.723	2.172	.030	.090

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

From our analysis, there is a very strong evidence (p < 0.05) of a difference between (SKM1-SKM3) the group who learn physically and were tested without objective questions during examination and those who learn through online platform, also without objective questions. The same applies to SKM1-SKM2 where apparently there is also difference between the method of learning as students from both sections were evaluated with objective assessments. On the other hand, there is notably no difference whether the students are being tested with objective questions or not during their online learning since the relationship between SKM2-SKM3 of recorded value p = 0.09 which is greater than 0.05.

4.4 M-estimator

Consider the following model:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \epsilon \tag{17}$$

where Y are the scores of the students, x_1 is the school represented by the students which is the first dummy variable, x_2 is the method of learning which is also the second dummy variable, and $x_1 x_2$ represents the interaction term between x_1 and x_2. Figure 1 below displays the R-programming output of rlm function that helps fit our model using an M estimator of Tukey's Biweight function.

```
Call: rlm(formula = SCORES ~ SCHOOL + METHOD + SCHOOL:METHOD,
 data = score,
    psi = psi.bisquare)
Residuals:
     Min       1Q   Median       3Q      Max
-48.0236  -9.2041   0.2542   8.6477  37.9764

Coefficients:
                       Value   Std. Error t value
(Intercept)            61.7458  1.8879    32.7056
SCHOOLSKM              -4.7223  2.6914    -1.7546
METHODONLINE           14.6065  2.7141     5.3818
SCHOOLSKM:METHODONLINE 11.3458  3.8702     2.9316

Residual standard error: 13.17 on 240 degrees of freedom
```

Figure 1: Output of rlm function displaying estimation values of each regression coefficient

R-output automatically generates dummy variables of our categorical data which are "SCHOOLSKM", "METHODONLINE", as well as the interaction variable, "SCHOOLSKM:METHODONLINE". This tells us that the base variable for School is "SKE", and base variable for Method is "face-to-face". Unfortunately, as we can see above, rlm function does not return any significance values of the coefficients thus restrained any further analysis on the significance of each of them. Therefore, another function named as stargazer function is used to aid us with the problem. Figure 2 below shows the output where the significance values are represented by the stars at the end of each coefficient.

```
\begin{table}[!htbp] \centering
  \caption{}
  \label{}
\begin{tabular}{@{\extracolsep{5pt}}lc}
\\[-1.8ex]\hline
\hline \\[-1.8ex]
 & \multicolumn{1}{c}{\textit{Dependent variable:}} \\
\cline{2-2}
\\[-1.8ex] & SCORES \\
\hline \\[-1.8ex]
 SCHOOLSKM & $-$4.722$^{*}$ \\
  & (2.691) \\
  & \\
 METHODONLINE & 14.606$^{***}$ \\
  & (2.714) \\
  & \\
 SCHOOLSKM:METHODONLINE & 11.346$^{***}$ \\
  & (3.870) \\
  & \\
 Constant & 61.746$^{***}$ \\
  & (1.888) \\
  & \\
\hline \\[-1.8ex]
Observations & 244 \\
Residual Std. Error & 13.170 (df = 240) \\
\hline
\hline \\[-1.8ex]
\textit{Note:}  & \multicolumn{1}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
\end{tabular}
\end{table}
```

Figure 2: Output of stargazer function displaying stars to indicate coefficients' significance

The range for the significance values is specified at the third line from the bottom. From our findings, only the SCHOOLSKM variable had a non-significant value, represented by a star. All three additional factors, the Intercept, METHODONLINE, and SCHOOLSKM:METHODONLINE, were found to be significant, with all p-values being less than 0.05 indicated by the three stars. Hence, connecting the information from both figures helps us to interpret that the interaction between the two variables is relatively significant with p-value lower than 0.01. Final model is as below:

$$\hat{Y} = 61.7458 + 14.6065x_2 + 11.3458x_1x_2 + \epsilon \tag{18}$$

Therefore, from our results of this robust regression of M-estimation with Tukey's Biweight function, we can deduce that the scores of the students have also statistically significant relationship with both the learning mediums and their respective schools.

5 Conclusion

In a nutshell, there exist statistically significant differences between the scores of those learning through virtual platform and those with physical interaction from Mann-Whitney Test. Kruskal-Wallis Test further detailed the differences occur between each section where the pairs are SKE1-SKE2, SKE1-SKM2, SKM1-SKE2 and SKM1-SKM2, which gives us an idea that coming from different schools might also affect their differences. This inference is then conveyed to application of M-estimation of robust regression where the interaction term between Method and School variables is found out to be statistically significant. Follow-up study by using Kruskal-Wallis Test resulted that the differences between the students' performances when additional objective evaluations are incorporated in their assessment is not statistically significant.

Overall, online learning is proved to yield improving outcomes compared to in-class delivery mode. Assessing the students with objective evaluation is optional. It is hoped that more research can be done on implementing the extension of M-estimators of robust regression such as S-estimators and MM-estimators for the data analysis as a recommendation for future research.

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