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Application of a Single-Case Research Design to Present the Effectiveness of Rehabilitation in the Clinic

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Abstract

Clinical benefits of rehabilitation are very difficult to present because of various factors such as very small sample sizes, no control comparison, or short period of intervention. However, clinical improvement can be presented with a single case study research design that is very interesting and challenging technique. Basic and advanced single-research designs can be performed in various patterns, for example, baseline (A) and intervention (B) phases [A-B], A-B-withdrawal (A') phases [A-B-A'], A-B-A'- new intervention (B') phases [A-B-A'-B], etc. In each phase, a line graph must be presented for changes using a trend line or split-middle method or mean and the standard deviation is shown. A trend or celebration line of data in the baseline period (A) should be drawn through the intervention phase (B). Then, the serial dependence or autocorrelation coefficient in each phase must be calculated by Barletta test, and the transformation of autocorrelation data should be performed when serial dependence occurs. Finally, clinically statistical improvement during intervention can be analyzed with the Bloom table, two-standard deviation band, paired t-test, binomial statistic, or C-statistical analysis. Therefore, single case study or cases of research design can be used to present the effectiveness of any intervention in the clinic.

**Keywords:** single-case research design, rehabilitation

1. Introduction

At present, the benefit of clinical research is very important in clinical practice. However, clinical research involving human patients or subjects has more varied bias and confounding

factors than experimental research [1]. A previous report claimed that common studies in clinical research had various designs such as case–control studies, cohort study, randomized controlled trials, reviews, and meta-analyses, the same as case reports [2]. Moreover, single-subject design also is used for practice-based primary care research, due to the limitation on condition, heterogeneity, and strict criteria, but with some interesting results [3]. Previous evidence reported that clinical research can be divided broadly into two types; observational and experimental [4]. Cross-sectional, case control, cohort, and ecological study are analytical, but prevalence surveys, case series, surveillance data, and analysis of routinely collected data are a type of descriptive study. Although the best clinical research is designed with a controlled group, low bias on inclusion criteria, and good statistical analysis protocol, the limitations on various pathological conditions and inconsistency among patients are presented, whereas the value of inspiring new ideas or explaining new results from techniques during rehabilitation is of clinical concern in multiple or single cases [5–7]. Therefore, effectiveness of rehabilitation in a rare or single case can be presented with descriptive data alone, as in a previous report that presented the effect of combined thoracic and backward lifting exercise at a thoracic kyphosis angle, and intercostal muscle pain, without any graphs, tables, or statistical analysis measurement [8]. However, better results of a single-case research design can be represented by visual graphs after data collection at either baseline or intervention phases, whereas efficiency of intervention also can be evaluated with a mean level and trend changes by comparing with baseline or prior interventions [9, 10]. Finally, significant effectiveness of intervention can be analyzed simply with the Bloom Table, paired t-test, or one-way ANOVA methods, if serial dependence or autocorrelation coefficient of data is not found (**Figure 1**).

The flow chart in **Figure 1** shows a simple series procedure for performing a single-case research, (1) collecting data in both baseline and intervention phases, (2) drawing the trend line and mean level in each phase, (3) checking the series dependency of data in each phase,
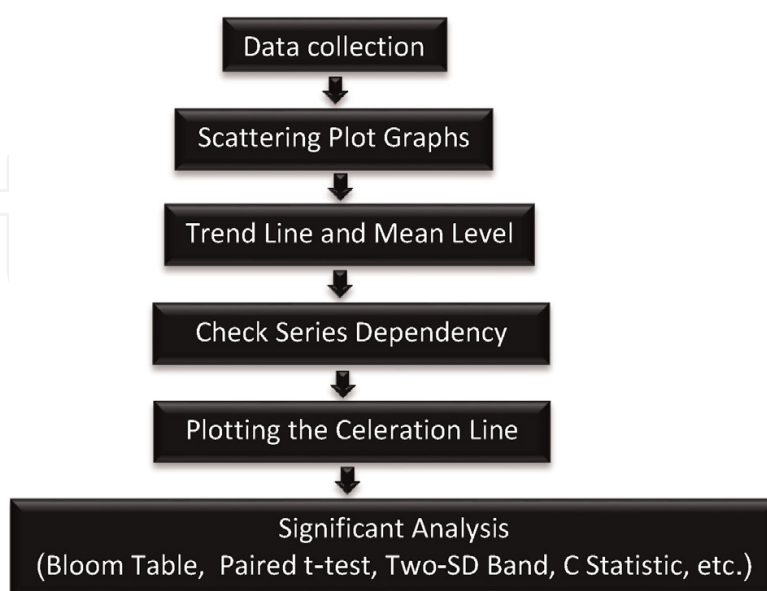

Figure 1. Flowchart of procedure on a single-case research design.

and (4) drawing the celeration line from the prior phase to the next one, and then analyzing statistically.

2. Research design

There has been a variety of single case research designs such as (1) AB, (2) reversal, (3) multiple baseline, and (4) alternating treatment [11]. The components of a single-case research design are composed of a series of interventions and frequency of assessment in multiple phases and various conditions. For instance, the effectiveness of a 7-day chest wall-stretching exercise in patients with chronic obstructive pulmonary disease (COPD) compared with 7 days in the baseline phase [12]. The same applies to 7-day pulmonary rehabilitation in patients with chronic scleroderma [13]. Therefore, various designs with a control period or baseline (A), intervention (B), withdrawn (A), or new intervention phase (B′) can be performed. Thus, a simple visual graph has been recommended with the following three designs (**Figure 2**).
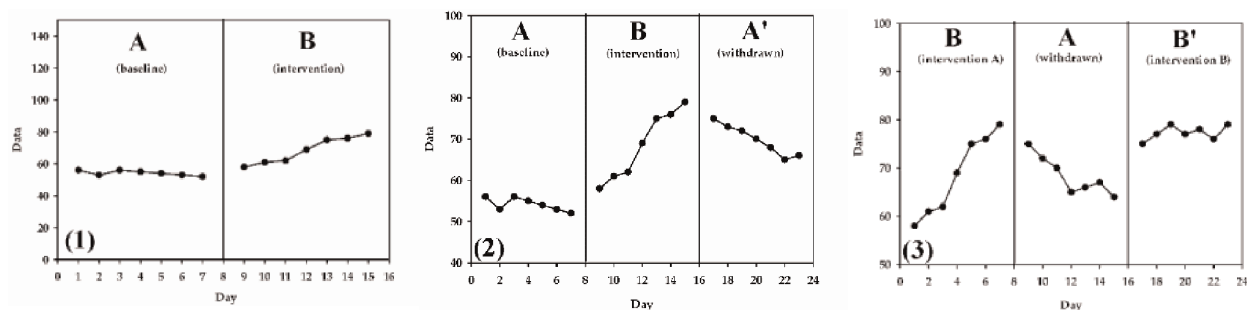
Figure 2. Visual graph presentation of a three-pattern design. Baseline and intervention phases (1), baseline-intervention-withdrawn phases (2), and intervention-withdrawn-intervention phases (3).

3. Data collection and presentation

In this design, the frequency of data collection has been suggested as at least three times or during individual periods in either the baseline or intervention phase [14], in order to present the change in trend in the baseline phase, whereas a previous report preferred an evaluation 6-8 times [15] as in **Table 1**, for example. The visual analysis involves determining the level, trend and stability of the data within in each phase, as well as immediacy of effect, consistency of data patterns, and overlap of data between baseline and intervention phases [16].

Presentation of the data or scores can be performed with scattering, plotted as a simple line graph for either single or multiple cases with a multiple baseline design, as in **Figure 3**.

Baseline phase						Intervention phase				
PImax	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
1	2	3	2	2	3	3	5	5	5	6
2	2	2	2	3	3	4	4	5	7	7
3	2	2	2	2	2	3	5	4	8	8
High value	2	3	2	3	3	4	5	5	8	8

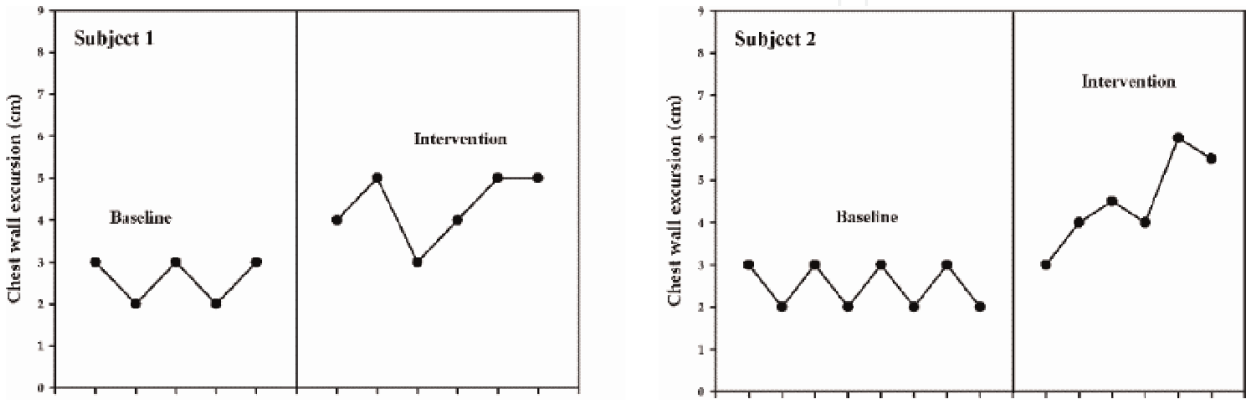**Table 1.** Chest wall excursion (cm) between baseline and intervention phases.

Figure 3. Line graph presentation of chest wall excursion (cm) in two cases that show the baseline and intervention phases with different scores in the baseline phase.

Presentation with a line graph has several advantages, for example, easy interpretation and understanding. Moreover, the bar graph of mean in each phase can be used.

The appropriate graphic methods can be applied to present data of changes in level, variability, trend, and slope [17] within each phase following the immediacy of effect, consistency of data patterns, and overlap of data between baseline and intervention phases [16]. For example, the mean levels of peak inspiratory pressure (PImax) between baseline (A), intervention (B), and withdrawn (A') is shown in **Figure 4(1)** and trend lines in **Figure 4(2)**. Trend lines within a phase can demonstrate the stability of scores in the baseline phase with constant trend, as well as acceleration and deceleration trend patterns in intervention and withdrawn phases, respectively.

Interpretation of the mean and trend line in each phase presents the meaning clinically, for example, chest wall excursion (**Figure 5(1)**), dyspnea scale (**Figure 5(2)**), vital capacity, diffused capacity of lung for carbon monoxide (DLCO), etc. **Figure 5(1)** shows the constancy of chest wall excursion before treatment, which then increases with a mean level higher (3.83 cm) than that at baseline (2.19 cm). Therefore, that intervention can increase chest wall excursion in the clinic. In addition, dyspnea scale changes in **Figure 5(2)** decrease from a mean of 5.6 in the intervention phase to 4.2 in the baseline phase.

The deleterious effect of interventions can be presented, as in **Figure 5(3)**. Vital capacity reduces and decelerates tendency during given treatment; therefore, that treatment does not

affect vital capacity. Finally, the last example of change in DLCO between baseline and intervention phases shows a slight increase of DLCO mean. Thus, that intervention can increase the DLCO slightly (**Figure 5(4)**).
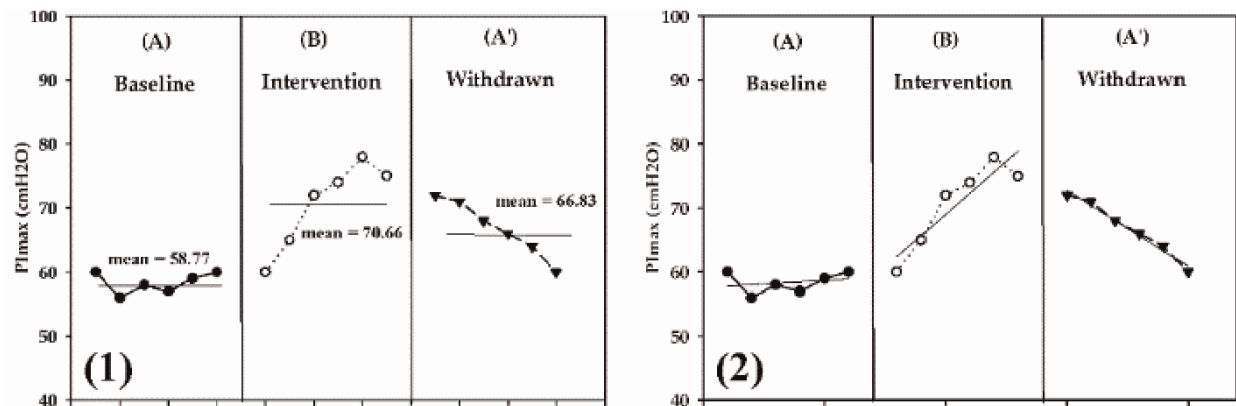
Figure 4. Demonstrated data of mean levels (1) and trend lines (2) within baseline (A), intervention (B), and withdrawn (A′) phases.
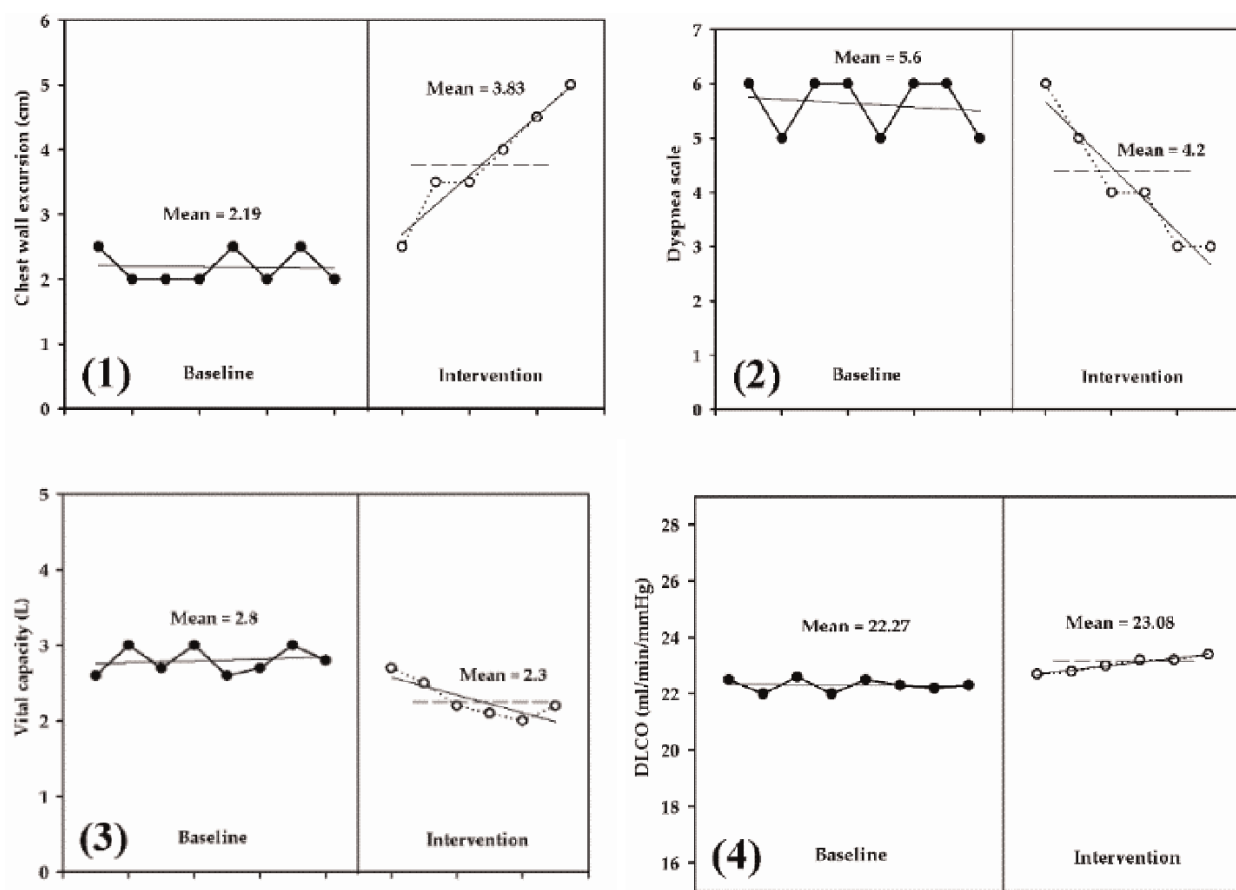
Figure 5. Graph lines of chest wall excursion (1), dyspnea scale (2), vital capacity (3), and diffusing capacity of lung for carbon monoxide (DLCO) (4) between baseline and intervention phases.

The trend line in each phase, especially between baseline and intervention phases, can show the effectiveness of rehabilitation using some techniques, for instance, the deceleration trend line of dyspnea (**Figure 5(2)**) and acceleration trend line of chest wall excursion (**Figure 5(1)**). Therefore, the effectiveness of rehabilitation in the intervention phase can be compared with the extended line from the baseline phase, which is called the **celeration line** as in **Figure 6**.

The celeration line can be found by the freehand [19], several semi-average [18], and least squares method, including computing in a specific program, such as SPSS or SigmaPlot.

The simple method of drawing the celeration line can be carried out by therapists using the semi-average [18] or "split-middle" method. For example, the data of 10 pain scores in the baseline phase; 4, 5, 4, 5, 6, 7, 6, 8, 7, and 6 have been recommended with 8–10 data in order to fit the celeration line more accurately [19, 20]. Therefore, the procedure of drawing a celeration line can be performed in the following steps:

Step 1: Plot the data (**Figure 7(1)**).

Step 2: Divide the data in half by drawing a solid vertical line and dividing each of the halves in half by drawing dashed vertical lines before plotting the median level of each half phase, so that the mean in the first half is 5 and 7 in the second half (**Figure 7(2)**).
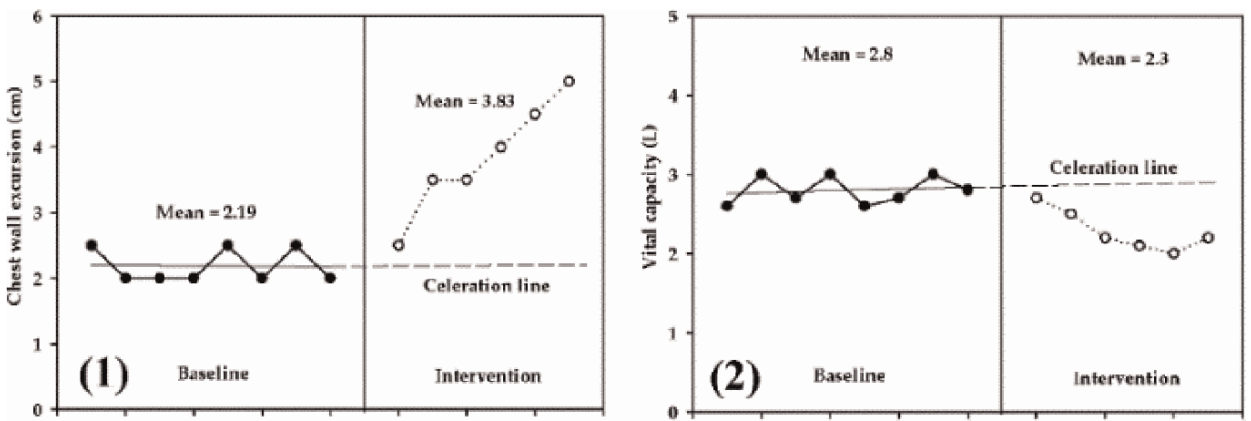
Figure 6. Line graphs showing the celeration line from the baseline phase of chest wall excursion (1) and vital capacity (2).
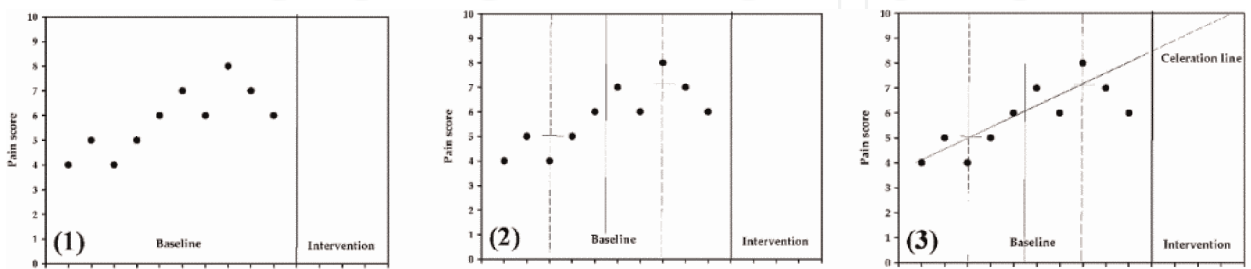
Figure 7. Plotting data in the baseline phase (1). The baseline phase is divided in half with a solid line, and each half phase is divided by dashed vertical lines with median horizontal lines (2). The celeration line is extended to the intervention phase (3).

Step 3: Finally, extend the celeration line from baseline to the intervention phase (**Figure 7(3)**).

On the other hand, the mean value of each half can be used for instant median value [18, 21].

Therefore, data presentation of the single-case research design is developed simply and under-stood with the mean level and trend changes in the baseline phase. In addition, the effectiveness of rehabilitation can be presented from the difference of mean level and trend line from the celeration line in the baseline phase. However, the effectiveness of rehabilitation in the intervention phase also can be compared under statistical procedure.

4. Statistical analysis

The statistical analysis must be performed as a series procedure. First of all, the data on autocorrelation or serial dependency must be evaluated so that it can violate the independence of error assumption of statistical tests [22]. Data or outcome especially should have no serial dependency on either baseline or intervention phases. Serial dependency basically means that temporally adjacent scores tend to be related to one another. For instance, the score of an individual subject for day 1 tends to predict that for day 2. A day-2 score can predict the day-3 score, etc. Previous study ranked lag 1 autocorrelation and assigned it to one of the three sets; autocorrelations ranging from 0.15 to 0.50 (low), 0.51 to 0.75 (moderate), and 0.76 to 0.94 (high) [23], which found the interaction between serial dependency and significance level. This meant that high serial dependency correlates with low significance. Therefore, the data within phase examination should have no autocorrelation (r) or serial dependency.

4.1. Serial dependency analysis

The procedure for calculating serial dependency is appraised by statistical calculation, called an autocorrelation coefficient, if the lag-1 autocorrelation for a series of performance is measured from a statistically significant evaluation ($p < 0.05$). For instance, the procedure is manual for calculating the autocorrelation coefficient in the baseline phase (**Table 1**), as in the following series:

Step 1: Calculate the mean of the scores in each phase with the sum of all data divided by total numbers.
Baseline phase: [2 + 3 + 2 + 3 + 3]/5 = 2.6

Intervention phase: [4 + 5 + 5 + 8 + 8]/5 = 6

Step 2: Find the difference values by minutes in each score (**Table 1**) with its mean.

Baseline phase	Intervention phase
Score-mean = difference value	Score-mean = difference value
2.0 − 2.6 = −0.6	4.0 − 6.0 = −2.0
3.0 − 2.6 = 0.6	5.0 − 6.0 = −1.0

Baseline phase	Intervention phase
Score-mean = difference value	Score-mean = difference value
2.0 − 2.6 = −0.6	5.0 − 6.0 = −1.0
3.0 − 2.6 = 0.6	8.0 − 6.0 = 2.0
3.0 − 2.6 = 0.6	8.0 − 6.0 = 2.0

Step 3: Calculate the sum of multiple first and second difference values from Step 2.

Baseline phase	Intervention phase
(−0.6) (0.6) = −0.36	(−2) (−1) = 2
(0.6) (−0.6) = −0.36	(−1) (−1) = 1
(−0.6) (0.6) = −0.36	(−1) (2) = −2
(0.6) (0.6) = 0.36	(2) (2) = 4
Sum = −0.72	**Sum = 5**

Step 4: Calculate the sum of the square of difference values from Step 2.

Baseline phase	Intervention phase
$(−0.6)^2 = 0.36$	$(−2)^2 = 4$
$(0.6)^2 = 0.36$	$(−1)^2 = 1$
$(−0.6)^2 = 0.36$	$(−1)^2 = 1$
$(0.6)^2 = 0.36$	$(2)^2 = 4$
$(0.6)^2 = 0.36$	$(2)^2 = 4$
Sum = 1.8	**Sum = 15**

Step 5. Calculate the autocorrelation coefficient (r) in each phase by dividing the sum value in Step 3 by the square sum of difference values in Step 4.

Baseline phase	Intervention phase
0.72/1.8 = 0.40	5/15 = 0.33

Step 6: Analyze the autocorrelation coefficient as statistically significant or not; a simple procedure called Bartlett test can be used. If the autocorrelation value (r) in Step 5 is less than 2/ √n (n = number of data), the nonsignificant autocorrelation within or in the phase is confirmed. Therefore, this example = 2/√5 is 0.894.

Baseline phase	Intervention phase
0.40 < 0.894	0.33 < 0.894

Final results of serial dependency calculation show that data in both phases have not demonstrated a significant degree of autocorrelation or serial dependency. Therefore, therapists may be confident in the results from disease stability in the baseline phase and intervention program. However, if the result of autocorrelation analysis shows significant serial dependency, transformation of autocorrelation should be performed again.

4.2. Transformation data

Due to significant serial dependency being presented in some phases during study, therapists cannot confirm changed results confidently from either the pathology or treatment [23]. For example, scores for dyspnea during 12 days of the baseline phase were 3, 5, 4, 5, 6, 6, 7, 8, 8, 11, 10, and 11, respectively.

Step 1: The mean score [3 + 5 + 4 + 5 + 6 + 6 + 7 + 8 + 8 + 11 + 10 + 11]/12 is 7.08.

Step 2: Difference values.

Score − mean	=	difference value
3.0 − 7.08	=	−4.08
5.0 − 7.08	=	−2.08
4.0 − 7.08	=	−3.08
5.0 − 7.08	=	−2.08
6.0 − 7.08	=	−1.08
6.0 − 7.08	=	−1.08
7.0 − 7.08	=	−0.08
8.0 − 7.08	=	0.92
8.0 − 7.08	=	0.92
11.0 − 7.08	=	3.92
10.0 − 7.08	=	2.92
11.0 − 7.08	=	4.92

Step 3: Calculate the sum of multiple first and second difference values.

(−4.08)(−2.08)	=	8.48
(−2.08)(−3.08)	=	6.41
(−3.08)(−2.08)	=	6.41

(−2.08)(−1.08)	=	2.24
(−1.08)(−1.08)	=	1.17
(−1.08)(−0.08)	=	0.08
(−0.08)(0.92)	=	−0.07
(0.92)(0.92)	=	0.85
(0.92)(3.92)	=	3.61
(3.92)(2.92)	=	11.45
(2.92)(4.92)	=	14.37
Sum	=	**54.99**

Step 4: Calculate the squared sum of difference values.

(−4.08)^2	=	16.65
(−2.08)^2	=	4.33
(−3.08)^2	=	9.49
(−2.08)^2	=	4.33
(−1.08)^2	=	1.17
(−1.08)^2	=	1.17
(0.08)^2	=	0.01
(0.92)^2	=	0.85
(0.92)^2	=	0.85
(3.92)^2	=	15.37
(2.92)^2	=	8.53
(4.92)^2	=	24.21
Sum	=	**86.92**

Step 5: Analyze the autocorrelation coefficient: 54.99/86.92 = 0.632. Analyze whether the autocorrelation coefficient is statistically significant or not, and $2/\sqrt{12}$ is 0.577 because$\sqrt{12}$ is 3.464 (n = 12). Therefore, these series data have significant serial dependency because 0.632 is more than 0.577. All data must be transformed by the first difference in transformation as below.

Step 6: The first score in the data is subtracted from the second, the second from the third, the third from the fourth, the fourth from the fifth, and so on, until all scores are fully completed: 3, 5, 4, 5, 6, 6, 7, 8, 8, 11, 10, and 12.

$3 − 5 = −2, 5 − 4 = 1, 4 − 5 = −1, 5 − 6 = −1, 6 − 6 = 0, 6 − 7 = −1, 7 − 8 = −1, 8 − 8 = 0,$ $8 − 11 = −3, 11 − 10 = 1,$ and $10 − 11 = −1.$

Thus, new data are −2, 1, −1, −1, 0, −1, −1, 0, −3, 1, and −1. When returning to calculate the serial dependency in Steps 1–5, the autocorrelation efficiency is 0. 51, which is less than 0.577. Finally, all new series data were added with a constant of any value such as 2, in order to avoid the minute value.

However, the transformation of data by the first transformation difference still failed, thus moving the average transformation to the second procedure in order to reduce the serial dependency in Step 7.

Step 7: The following moving average method reduces the serial dependency that consists of simply plotting the mean values between two adjacent data points over the entire series data.

Score				Transformed score
3 + 5	=	8/2	=	4.0
4 + 5	=	9/2	=	4.5
6 + 6	=	12/2	=	6.0
7 + 8	=	15/2	=	7.5
8 + 11	=	19/2	=	9.5
10 + 11	=	21/2	=	10.5

Then, the new data from 12 to 6 of 4.0, 4.5, 6.0, 7.5, 9.5, and 10.5 will be returned for calculating the autocorrelation coefficient (r) in Steps 1–5. The result of the new autocorrelation coefficient calculation is 0.56, which is less than 0.82 (2/√6). Therefore, the data do not present serial dependency.

4.3. Statistical evaluation

4.3.1. Standardized statistic method

When the non-serial dependency or autocorrelation is not presented in each phases, confidential results of rehabilitation can be implied without any confounding factors from diseases or condition of auto-recovery. Finally, the procedure for identifying the statistical difference between intervention and baseline or control can be evaluated by various methods. Analysis of variance (ANOVA), F-test, and t-test between phases are widely familiar to researchers and clinicians, for example, comparing the data of expiratory tidal volume (VTE) during 10 days on a mechanical ventilator during chest physical therapy with the previous 10 days of non-treatment. The visual graphic shows the mean, autocorrelation, and trend line (**Figure 8(1)**), whereas bar graphs with a significant level calculated under the nonparametric paired t-test were presented (**Figure 8(2)**).

Before the CPT phase: 352, 350, 323, 349, 345, 350, 352, 348, 360, 354 (mean = 347.9 mL).

During the CPT phase: 364, 371, 378, 380, 410, 425, 429, 485, 501, 515 (mean = 425.8 mL).
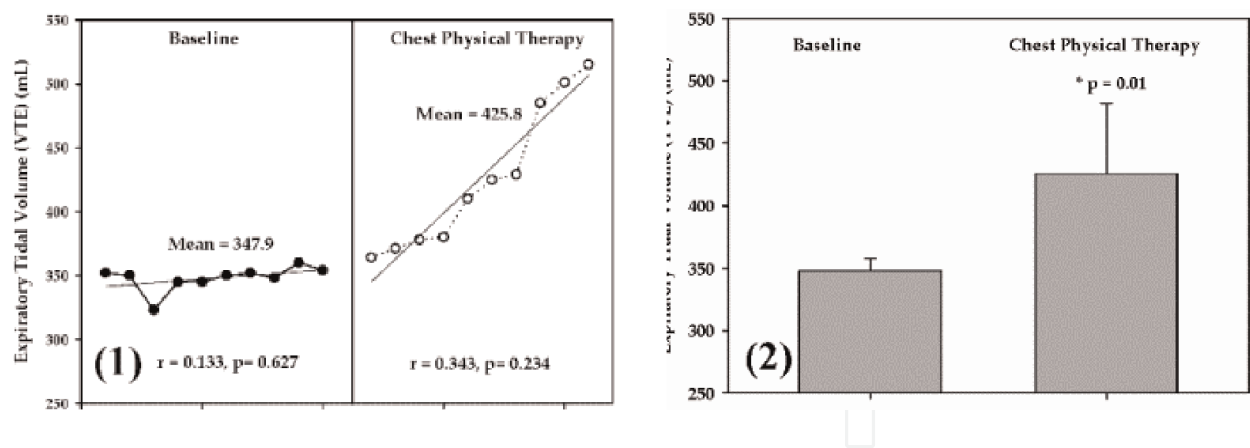
Figure 8. Line graphs of expiratory tidal volume (mL) at baseline and intervention by chest physical therapy phase (1) and t-test analysis from the Wilcoxon signed-rank test in the SPSS program (2).

### 4.3.2. Statistical analysis with the celeration line

When the celeration line is approached from the baseline to intervention phase, the changes should be stationary if the pathology is stable, whereas some celeration lines from baseline may decelerate muscle mass from prolonged bed rest or accelerate dyspnea from secretion obstruction. A previous report claimed that the celeration line during the intervention phase was the same as that in the baseline phase, indicating no beneficial effect from treatment [24], whereas 50% of the data points in the intervention phase fell or were below the celeration line from the baseline phase, which reflected beneficial clinical effect from treatment.

Two methods can be used to determine statistically significant changes. One method is using the probability table presented by Bloom [25] (**Table 2**), and the other is computing a simple binomial test.

Proportion during baseline	Number of treatment observations				
	4	6	8	10	12
0.10	3	3	3	4	4
0.15	3	3	4	4	5
0.20	3	4	5	5	6
0.25	4	4	5	6	7
0.30	4	5	6	6	7
0.35	4	5	6	7	8
0.40	4	5	6	8	9
0.45	4	6	7	8	9
0.50	4	6	7	9	10

Modified from Bloom [25], p. 203. Determined by use of the one-tailed test; $p < 0.05$.

Table 2. Number of treatment observations above the celeration line that are required to demonstrate a statistically significant effect.
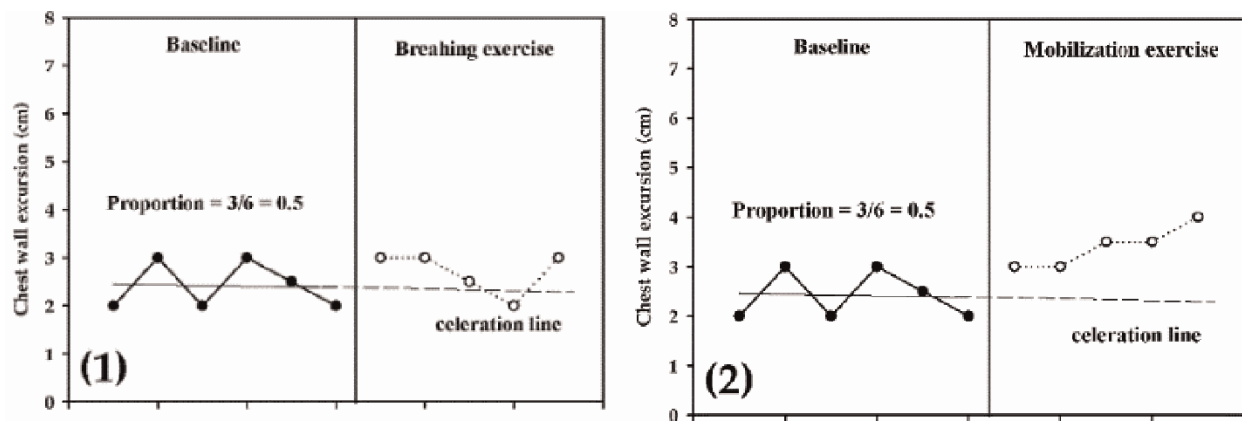
Figure 9. Comparative data of chest wall excursion (cm) between interventions: breathing exercise (1) and mobilization exercise (2).

4.3.3. Statistical analysis using the Bloom table

The method for using the Bloom Table (**Table 2**) for statistical analysis is performed in the following steps, for example, chest wall excursion with two different treatments in **Figure 9**.

Step 1: Calculate the proportion during the baseline phase, for example, in **Figure 9**. From a total of six data points, locate three points above the trend line, so the proportion is 0.6.

Step 2: Draw the extending or celeration line to the treatment phase.

Step 3: See that the first column is 0.50 in the Bloom Table and the number of treatment observations is 5. The intersection of these two values is approximately 5.

Step 4: Figure 9(1) has only four points above the trend line, whereas **Figure 9(2)** has all five points above trend line. Therefore, the mobilization exercise shows significant changes in the clinic, but the breathing exercise does not affect chest wall excursion.

4.3.4. Statistical analysis with the two-standard deviation band method

This method is a semi-statistical approach or "statistical rule of thumb" and easily performed. A previous report indicated that at least two data points fall outside the two-standard deviation band during the intervention phase, which presents a statistically significant change in intervention [26]. Nowadays, there are many computing programs that can calculate the mean and standard deviation, for instance, Microsoft Excel, SigmaPlot, etc. Therefore, a simple and quick calculation on these data can be performed, for example, calculating the data of systolic blood pressure (mmHg) between the baseline phase and exercise period.

Baseline phase: 120, 123, 121, 122, 125, 122, 123, 122, 121, 122 (mean = 122.21, SD = 1.45)

Exercise period: 120, 119, 116, 115, 117, 114, 100, 101, 100, 102 (mean = 110.4, SD = 8.45)

Thus, two-standard deviation (SD) values in the baseline phase can be calculated with two times of SD (1.45 × 2 = 2.9). The upper band above the mean is a sum of 122.1 and 2.9

(122.1 + 2.9), and the lower band below the mean is 122.1 minutes 2.9 (122.1 − 2.9). Therefore, final levels of the 2-SD band are 125 and 119.2, which are drawn in **Figure 10(1)** and **(2)**.

4.3.5. Statistical analysis with the binomial test

This method was demonstrated by Kazdin [15] and White [20]. The formula for computing was based on the binomial test $\binom{x}{n}$ p^n, where n is the number of data points in the intervention phase, x is the number of data points above (or below) the celeration lines, and p is the probability of obtaining $\times$ data points above or below the projected celeration line [27]. Therefore, the binomial test from **Figure 11** can be computed by n = 5, X = 4, and p = 0.5, with results in statistical probability of p < 0.05.

Null hypothesis (Ho) = data points in the intervention phase being more than 5 in 10.
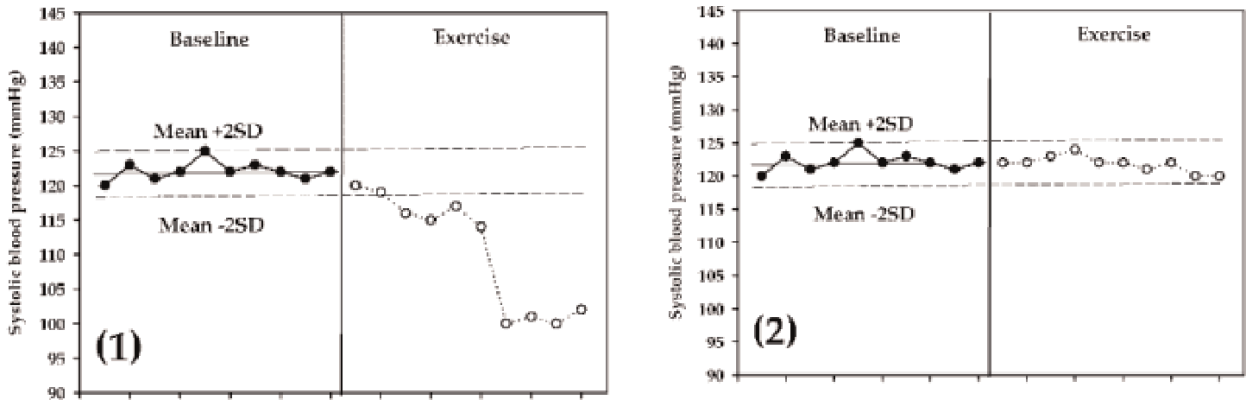
Figure 10. Line graph depicting the 2-SD band method for identifying the statistical significance between two subjects. Different results of exercise occurred in the two subjects, with the first subject showing most of the points (8 in 10 points) below the 2-SD band; thus, it can be concluded that the exercise reduces systolic blood pressure significantly (1), whereas 10 points are located within the 2-SD band in the second subject, which involves nonsignificant change when exercise is implicated (2).
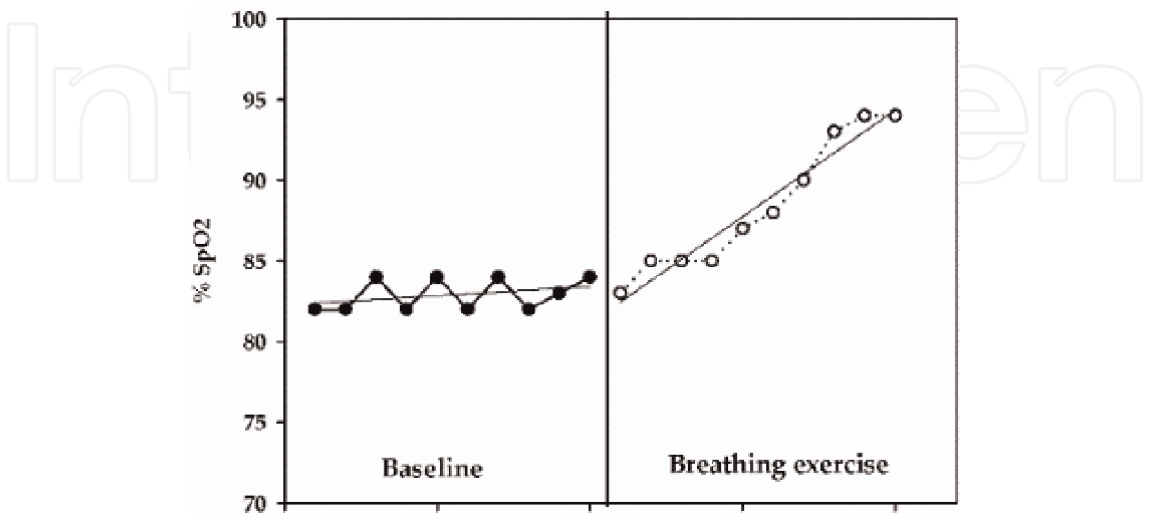
Figure 11. Line graph showing the data in baseline and breathing exercise phases.

	Category	N	Observed Prop.	Test Prop.	Aym.	Sig (1-tailed)
Data	Group 1	1.00	4	0.8	0.50	0.375
	Group 2	0.00	1	0.20		
			5	1.00		

Note: Group 1 is the number of data points above the celeration line, whereas Group 2 is the number of data points below the celeration line from the baseline phase.

Table 3. Result of the binomial test from SPSS analysis.

Alternative hypothesis (H1) = data points in the intervention phase being less than 5 in 10.

The result of the binomial test in **Table 3** shows an asymmetrically significant value (0.375) of more than 0.05, which means acceptance on the null hypothesis.

4.3.6. Statistical analysis with C statistic

The C statistic method was proposed by Bloom and Fisher (1975) [21] and Tryon (1982) [28] as a single-case research design and also reported by Caetano et al (2018) [29]. There are seven steps in using C statistic with example data shown below.

Example: data of % oxygen saturation ($\%SpO_2$) in a postoperative cardiac patient:

Baseline phase: 82, 82, 84, 82, 84, 82, 84, 82, 83, 84

Breathing exercise: 83, 85, 85, 85, 87, 88, 90, 93, 94, 94

Step 1: Each data point in the baseline phase is subtracted from its adjacent successor data, for example, the first from second, second from third, etc. until all of the scores in the baseline phase are used.

Step 2: Each value from Step 1 is squared and the sum repeated.

Step 1			Step 2		
82 − 82	=	0	$(0)^2$	=	0
84 − 82	=	2	$(2)^2$	=	4
84 − 82	=	2	$(2)^2$	=	4
84 − 82	=	2	$(2)^2$	=	4
83 − 84	=	−1	$(-1)^2$	=	1
			Sum	=	**13**

Step 3: The mean value of the baseline points is calculated.

82 + 82 + 84 + 82 + 84 + 82 + 84 + 82 + 83 + 84 = 829/10 = 82.9

Step 4: The value of mean-difference for each set of data is calculated by subtracting each raw score from the mean value of squared results before summing up the squared mean difference.

82	−	82.9	=	−0.9	$(-0.9)^2$		=	0.81
82	−	82.9	=	−0.9	$(-0.9)^2$		=	0.81
84	−	82.9	=	1.1	$(1.1)^2$		=	1.21
82	−	82.9	=	−0.9	$(-0.9)^2$		=	0.81
84	−	82.9	=	1.1	$(1.1)^2$		=	1.21
82	−	82.9	=	−0.9	$(-0.9)^2$		=	0.81
84	−	82.9	=	1.1	$(1.1)^2$		=	1.21
82	−	82.9	=	−0.9	$(-0.9)^2$		=	0.81
83	−	82.9	=	0.1	$(0.1)^2$		=	0.01
84	−	82.9	=	1.1	$(1.1)^2$		=	1.21
					Sum		=	**8.9**

Step 5: The value from Step 4 is multiplied by 2: $8.9 \times 2 = 17.8$.

Step 6: The C score is computed using the formula.

$$C = 1-[\textit{value from step 2}/\textit{value from step 5}]$$
$$= 1-[13/8.9]$$
$$= 1-1.46$$
$$= -0.46$$

Step 7: The standard error for the C statistic is computed using the formula.

Standard error = $\sqrt{(n-2)/(n-1)(n+1)}$, in which n = the number of data in the series data from which the C statistic is computed.

Standard error = $\sqrt{(10-2)/(10-1)(10+1)} = \sqrt{8/99} = \sqrt{0.0808} = 0.284$

Step 8: In determining whether the C statistic is significant, a Z score is computed by dividing the C statistic value from Step 6 by the standard error from Step 7.

$$Z = \textit{step 6}/\textit{step 7}$$
$$= -0.46/0.284$$
$$= -1.62$$

Step 9: Statistical analysis: for any series data with 10 data points, a Z of 1.64 or more is significant at a level of $p < 0.05$. The results of Z calculation in the baseline phase shows −1.62, which is less than the required 1.64, indicating that the trend does not exist.

Step 10: Data in the intervention phase are included with the baseline phase and completed as in Step 2.

$82 - 82 = 0$	$(0)^2 = 0$
$84 - 82 = 2$	$(2)^2 = 4$
$84 - 82 = 2$	$(2)^2 = 4$
$84 - 82 = 2$	$(2)^2 = 4$
$83 - 84 = -1$	$(-1)^2 = 1$
$83 - 85 = -2$	$(-2)^2 = 4$
$85 - 85 = 0$	$(0)^2 = 0$
$87 - 88 = -1$	$(-1)^2 = 1$
$90 - 93 = -3$	$(-3)^2 = 9$
$94 - 94 = 0$	$(0)^2 = 0$
	Sum = **27**

Step 11: The mean value for the baseline points is calculated: $82 + 82 + 84 + 82 + 84 + 82 + 84 + 82 + 83 + 84 + 83 + 85 + 85 + 85 + 87 + 88 + 90 + 93 + 94 + 94 = 1713/20 = 85.65$.

Step 12: The value of the mean-difference for each set of data is calculated by subtracting each raw score from the mean value of squared results before summing up the squared mean difference.

82	–	85.65	=	−3.65	$(-3.65)^2$	=	13.32
82	–	85.65	=	−3.65	$(-3.65)^2$	=	13.32
84	–	85.65	=	−1.65	$(1.65)^2$	=	2.72
82	–	85.65	=	−3.65	$(-3.65)^2$	=	13.32
84	–	85.65	=	−1.65	$(1.65)^2$	=	2.72
82	–	85.65	=	−3.65	$(-3.65)^2$	=	13.32
84	–	85.65	=	−1.65	$(1.65)^2$	=	2.72
82	–	85.65	=	−3.65	$(-3.65)^2$	=	13.32
83	–	85.65	=	−2.65	$(-2.65)^2$	=	7.02
84	–	85.65	=	−1.65	$(1.65)^2$	=	2.72
83	–	85.65	=	− 2.65	$(-2.65)^2$	=	7.02
85	–	85.65	=	−0.65	$(-0.65)^2$	=	0.42
85	–	85.65	=	−0.65	$(-0.65)^2$	=	0.42
85	–	85.65	=	−0.65	$(-0.65)^2$	=	0.42
87	–	85.65	=	1.35	$(1.35)^2$	=	1.82
88	–	85.65	=	2.35	$(2.35)^2$	=	5.52
90	–	85.65	=	4.35	$(4.35)^2$	=	18.92
93	–	85.65	=	7.35	$(7.35)^2$	=	54.02

94	–	85.65	=	8.35	$(8.35)^2$	=	69.72
94	–	85.65	=	8.35	$(8.35)^2$	=	69.72
					Sum	=	**312.55**

Step 13: The value from Step 12 is multiplied by 2: 312.55 × 2 = 625.1.

Step 14. The C score is computed using the formula.

$$C = 1 - [\textit{value from step } 10/\textit{value from step } 13]$$
$$= 1 - [27/625.1]$$
$$= 1 - 0.043$$
$$= 0.957$$

Step 15: The standard error for the C statistic is computed using the formula.
Standard error = $\sqrt{(n-2)/(n-1)(n+1)}$, in which n = the number of data in the series data from which the C statistic is computed.

Standard error = $\sqrt{(20-2)/(20-1)(20+1)} = \sqrt{18/399} = \sqrt{0.045} = 0.212$

Step 16: In determining whether the C statistic is significant, a Z score is computed by dividing the C statistic value from Step 14 by the standard error from Step 15.

$$Z = \textit{step } 6/\textit{step } 7$$
$$= 0.957/0.212$$
$$= 4.514$$

Step 17: Statistical analysis: for any series data with 20 data points, a Z of 1.64 or more is significant at a level of p < 0.05. The results of Z calculation in the baseline and intervention phases show 4.514, which is more than the required 1.64. This presents a statistically significant trend across the baseline and intervention phases, or the breathing exercise in this case affects oxygen saturation in the clinic when compared to the baseline phase.

5. Discussion and critical point for a single-case research study

All details and data on examples show the procedure for presenting a single-case research study, due to the limitation on conditions, rare cases, and interesting treatment [3]. A basic procedure of a single-case design, with visual graphs of 6–8 data points in each phase [15], including mean level and cerelation line in baseline phase, can be presented [8]. When the data in each period at either baseline or intervention have no series dependency, a clinically significant difference of the treatment can be evaluated by comparing the baseline or pre-treatment using the Bloom Table, C statistic, or paired t-test [22, 25, 28, 29]. Moreover, the different types

of single-case experimental designs as alternating treatment, introduction/withdrawal designs, or multiple baseline designs are very interesting in physical and rehabilitation medicine [30]. However, an update on evidence in using a single-case design reported that it risks a bias tool (SCD RoB) based on current conceptualizations of biases, as well as the Cochrane risk of bias criteria. Therefore, contemporary single-case design quality should be applied for demonstrating and providing initial validation in research using such a design [31]. In order to demonstrate a single-case research study, the clinical details or characteristics of a subject must be presented as in previous study; such as illness history, medical diagnosis, laboratory results, and prior medical treatments during 7 days of pre-treatment, during treatment and/or posttreatment with an ABA study design. It is important that the condition of a patient, its stability or constancy, is reported for at least 7 days in COPD patients [12]. Their arterial blood gas (ABG), complete blood count (CBC), blood chemistry, liver function test, chest X-ray, and sputum culture also are reported. The results presented the autocorrelation values in each phase, which was less than $2/\sqrt{7}$ or 0.756. Therefore, it can be assumed that the results have no autocorrelation within the data, so changes in the data did not reflect the time dependence or pathological condition [22]. In addition, a previous study on a scleroderma patient having short-term chest physical therapy (CPT) for 7 days compared pre-treatment with an A-B design and showed that CPT significantly reduced the dyspnea score and respiratory rate and increased chest expansion and maximal inspiratory mount pressure (PImax) by using Bloom Table analysis [13]. Therefore, both previous studies present the effectiveness or benefits of rehabilitation in specific patients. Thus, in order to present the effectiveness of therapy or rehabilitation, all details of treatment also should be cleared and more details given such as techniques, frequency, intensity, and timing. When specific treatment is performed, the outcomes should be recorded daily before statistical analysis. For good data presentation, graph lines with scattered plotting, mean level, and autocorrelation must be presented in each phase. Finally, the clinical effectiveness of treatment must be shown by using the statistical protocol, such as the celeration line from the baseline to treatment phase and Bloom Table analysis. In addition, the statistic nonparametrical paired t-test or one-way ANOVA or C statistic can be used for confirmation as same as in a previous review meta-analysis suggestion [32].

6. Conclusion

The effectiveness of rehabilitation can be seen under a single-case research design as well as in practice of psychology research [33]. Firstly, data collection should be performed at least 5 days before starting intervention or treatment in order to obtain higher stability for the condition of the patient. Secondly, scattering the data from baseline and intervention with visual graph lines must be carried out. Thirdly, trend lines and the mean values in each phase should be calculated and plotted. Fourthly, series dependency or autocorrelation coefficient must be calculated and indicated on the graph. Finally, statistical analysis of the effectiveness of treatment can be performed by comparing with the celeration line, which has been drawn manually using the spilt-middle method or fit curve from baseline phase, and underlining the Bloom Table. Moreover, the nonparametrical paired t-test or binomial test can be used. Although

there are some limitations in this method, due to the small data collection and series dependency of data within each phase, it has easy-to-understand visuals and shows the trend. Therefore, a single-case research design is one of the many statistical protocols that can be applied for clinical scientists or therapists in order for them to represent the effectiveness of treatment in rare cases and present interesting results. Furthermore, the results of a good research design can be developed into a standardized statistical model, with a larger sample size, control subjects, and parametric statistical protocol in the future.

Conflict of interest

All authors claim no conflict of interest.

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