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The value of z-scores in social work supervision and practice

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ABSTRACT: Z-scores are presented as a tool to enable a clinical supervisor or practitioner to monitor a client's multiple factors over time. A review of the statistics of normal distributions if presented within the context of practice evaluation. Three advantages of z-scores exist. 1) Multi-dimensional aspects of a client are clarified; 2) practitioner develops a clearer understanding of complex problems; 3) progress within the passage of time is illuminated. Three practice examples are provided that demonstrate the versatility z-score monitoring designs. Guidance is given to direct the most efficient manner to apply z-scores to everyday practice.

Keywords: z-scores, practice evaluation, supervision, monitoring designs, statistics

1. Introduction

It is rare for clinical practitioners to escape their education or training without successfully completing at least one statistics course. Equally rare, is for practitioners to recall the seemingly esoteric dimensions of this most dreaded course (Marson, 2007). One highly forgettable moment in a statistics course is the introduction to z-scores. At first blush, the untutored eye will envision z-scores as nothing more than a framework for developing an appreciation for the normal distribution and to comprehend the meaning of a standard deviation. However, the employment of z-scores has demonstrated great usefulness in a wide range of professional activities.

The functionality of z-scores can be found in nearly every discipline. In business, z-scores are used to assess impending bankruptcies (Singh & Singla, 2019). Cleverley et al (2018) and older editions employ z-scores on a macro level as a tool for annually assessing the state of the hospital industry. In assessing the progression of childhood obesity, Gibson et al. (2016) transformed multi-level variables to z-scores to undercover meaningful patterns within family

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structures. Martinez-Millana et al. (2018) employed z-scores to assess growth and nutritional status for children*.* In medicine, z-scores calculations are used in the analysis and assessment of quantitative electroencephalography (Thatcher, & Lumbar, 2008). As in other disciplines, the employment of z-scores has a great deal of practical application in clinical social work practice, supervision and analysis of treatment.

Why use z-scores in social work practice? The answer lies within the rarely addressed conflict between practicing social workers and academic social workers (Marson, 2005). Starting in 1903, a rarely discussed contradiction emerged between professors and practitioners. Although oversimplifying the conflict, it can be best described as the inability for academicians to offer evaluative tools that fit the *real* social work practice environment. Academicians were preoccupied with compliance with statistical assumptions of measurement tools. The sad fact is that statistical assumptions are rarely met in real social work practice. Social work (and social science in general) is not physics.

How does a practitioner address the problem of assessment? The answer lies within the acknowledgement that there is no single effective or appropriate protocol to assess *all practice*. An evaluate protocol must meet the needs of the practice situation. Thus, the clinical social worker needs to be armed with a wide range of evaluations tools that will be appropriate with a wide variety of practice environments. One of the many evaluative tools is the employment of z-scores.

Here, we offer a refresher course in the use of z-scores by defining them mathematically while demonstrating their practical application for clinical social workers. Three illustrations are offered. In the past, the major limitation of the use of z-scores within clinical practice is the length of time it takes to complete the calculations. Learning and paying for statistical software is expensive, time-consuming and frustrating. Within this work, we present how Excel ® (which is a standard software component on most computers) can be used to transfer raw data to z-scores and produce complex graphics in a manner in minutes.

A Short Course in Z-scores

Clinical social workers became reacquainted with standard deviations with publication of the first edition of Bloom and Fischer (1982) and the several editions that followed. Here the authors illustrated the two-standard deviation approach for single system designs. The instruction of single system designs is a common component to most social work curricula.

Thus, the formula is familiar: $s = \sqrt{\frac{\sum(x\text{-}x)^2}{n\text{-}1}}$

Without the use of a programmable calculator or a computer, the clinical social workers with a weak background in statistics will take 45 minutes to complete the calculations. A programmable calculator or a computer can complete the task within a nanosecond.

A z-score is nothing more than a measure of standard deviation units. Thus, a z-score of +1.5 represents a location within a normal curve that is exactly between 1½ standard deviations on the right-hand side of the mean; while, -1.5 represents a location within a normal curve that is exactly between 1½ standard deviations on the left hand side of the mean. Excellent, humorous and more detailed explanations of z-scores can be found in Gonick and Smith (2015); while more serious but user-friendly presentation can be found in the works of Graham (2017), Jaisingh (2006), Moore, Notz, & Flinger, (2017), Sauro (2018) and Salkind (2005). The formula for a z-score is simple:

$$Z = \frac{x - \mu}{\sigma}$$

The problem that clinical social workers have with this formula is the denominator. The Greek letter *sigma σ* represents the standard deviation for the population. In order to be useful to clinical social workers, hundreds of z-scores must be calculated and graphed. Excel ® can calculate thousands of z-scores in a nanosecond. After some experience, a professional appearing graphic illustration of the relationship among data converted to score can be completed in about three minutes.

Z-scores are most helpful within the context of "Monitoring Designs" (see Alter and Evans, 1991; pages 89-99). In particular, z-scores can be employed in the evaluation of a client's progress, the identification of patterns that can direct clinical practice and can uncover obstacles that prevent successful treatment. The use of z-scores within monitoring designs are limited to the assessment of patterns with at least *two* factors that have treatment relevance. Three examples are offered.

Example 1: Evaluating Social Work Practice Outcomes

Alter and Evens (1990; p. 91-2) offer a case study of Christine Wilder, but does *not* employ z-scores to clarify the evaluation of Chris' progress. Chris was referred to a school social worker because of serious behavioral problems. The clinical supervisor identified Chris' frustration related to her lack of academic success as the central problem. As a result, she was given special attention to improve her vocabulary. Each day, the new words she learned were recorded: 8, 9, 6, 20, 21,22, 23, 23, 30, 31, 29, 40,63, 66, 98,101, 121, 121,123,129, 141,151,149, 152, 152, 159, 161, 176, 188. Within the same timeframe, Chris received the following demerits: 12, 11,13, 14, 12, 13, 11, 12, 13,14,10,10,11, 8,7,9,8,9, 8, 8,7, 9,7,6, 6, 6,7,4, 5, 4, 3, 3,3, 3, 3,3,3, 2,4,2,2, 2,2,1,0,0, 0,0,0, 0, 0, 0, 0,0 ,0, 0,1,0. Alter and Evens (1990) include data for 30 days of improved word recognition and 60 days for assessing disruptive acts.

Furnished by Alter and Evans (1991), Figure 1 illustrates both sets of data within a single graph, but it is a jumble of incoherency. When we take Alter and Evans' data and the transform their data sets to z-scores (Figure 2), greater clarity is offered. Figure 2 demonstrates that intervention has been exceedingly successful. As school success improves, disruptive behavior decreases. The positive change cannot be seen in Figure 1.

Figure 1

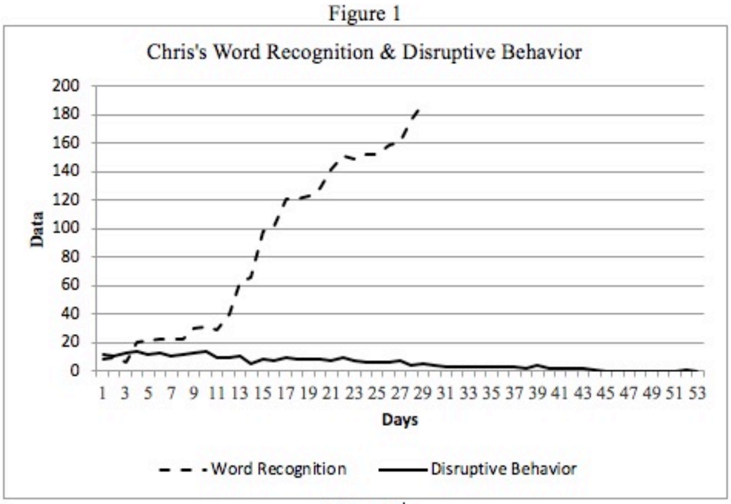
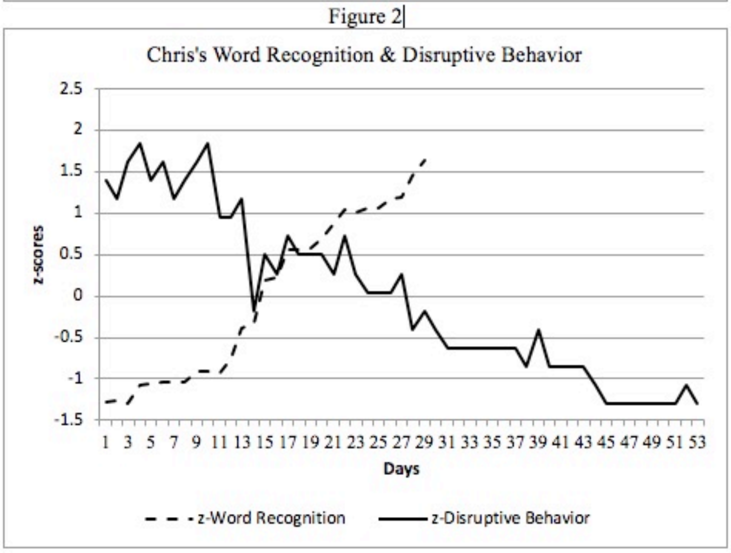


Figure 2



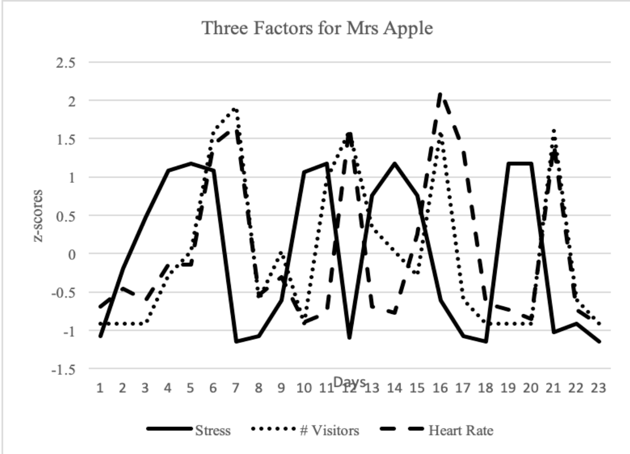
A detailed analysis demonstrates that the z-scores offers superior method for practice evaluations when compared to assessing raw data and even a correlation coefficient for two reasons. The clinical supervisor has clear evidence that Chris has improved under the care of the school social worker. First, the calculation of *r* requires equal number of data points for word recognition and disruptive behavior, would prohibit the use of all the data. All of the data points for disruptive behavior after day 31 would have to be excluded. Second, the *r* for the data excluding points after day 31 equals -.86. Although this is an impressively high correlation coefficient, the graphic illustration would have much more substantive meaning to the clinical supervisor or in the case of Chris, the principal of the school. In addition, nothing would prohibit the correlation coefficient from being included in the progress notes. The graphic illustration of the z-scores become a powerful source for the assessment of improvement for Chris and the quality of the intervention directed by the school social worker.

Example 2: Changing the Focus of Intervention

A BSW graduate obtains employment at a multi-level campus for older adults. The facility offers the widest possible living arrangement that are legally possible. An older adult is able to sign a contract for living arrangements in a condo and be assured that as health declines continuation to the skilled nursing care is available. An inexperienced social worker was perplexed with the general affect and strange facial expression from Mrs. Apple who resided in the independent living section of the facility. The process of his observations slowly unfolded into a concern that there was a strange relationship between family visits and stress.

His observational conjecture led him to assess two types of stress measures on a daily basis. These included the Index of Clinical Stress (Abell, 1991), resting pulse rate in conjunction with the number of family members that visited. Each day after breakfast, he administered the Index of Clinical Stress immediately after the nurse took and recorded the resting pulse rate. At the end of the day, he recorded the number of family members who visited then loaded the numbers into Excel. The Index of Clinical Stress has an outcome measure ranging between 1 to 100 and has sufficient validly research (Springer, Abell & Nugent, 2002; Springer, Abell & Hudson, 2002) with successful usage with elderly samples (Williams, Tappen, Wiese, Newman, Corbett, Pinos, Curtis, & Murray, 2016). The optimum resting pulse rate for persons over 70 range from 75 to 128 BPM (beats per minute). The visitation range varied from 0 to 8 family members visiting in a single day.

The raw data were collected and loaded into Excel. The data was transformed to z (or standardized) scores then inserted into a line chart as illustrated in Figure 3.



The BSW social worker and nurse were alarmed at the high resting pulse rate each time family members visited Mrs. Apple. Her average BPM during family visits was 130 while without family visitors her average BPM was 78 BPM. The most remarkable aspect found within Figure 3 is that the Index of Clinical Stress predicted family visitation and the BPM. When the Index of Clinical Stress was elevated, the data suggests that family visitation would soon follow with a corresponding and alarming increase in BPM.

In the process of interviewing Mrs. Apple and studying her social history, the BSW social worker speculated that her family members wished to accelerate Mrs. Apple's death in order to acquire her estate before all of her financial resources could be claimed by her health care expenses. It was an incredibility difficult story for the BSW social work to accept. As a result, the social worker contacted the clinical supervisor and learned that his initial speculation was not unusual. Such situations have been formally documents (Marson, 2019). Because of the z-score transformation and consultation with the clinical social worker was made, a policy change was instituted regarding the number of visitors per day. The BSW continued to monitor Mrs. Apple's Index of Clinical Stress, her BPM and the number of visitors. The policy changes greatly improved the stress readings for Mrs. Apple's.

Example 3: Detective Work

This case scenario demonstrates the application of z-score transformation for social work practice in a hospital setting. Hospitals have the capacity to closely monitor a client's change over time. Clinical social work practice in such facilities provides a great opportunity to use z-scores for evaluating client progress and identifying additional problems. Z-score transformation enables the clinician to simultaneously contrast the changes among different variables. In this case, Misti who has been diagnosed with anorexia is hospitalized. Her ideal weight is 120 pounds. She was admitted at 85.6 pounds. Three variables with very different metrics are monitored on a daily basis.

- Misti is weighed every day immediately following supper.
- Misti's daily caloric intake is calculated and recorded for the hospital chart during the third shift.
- During group therapy, a social worker is assigned the task of making a slash mark each time a patient makes a statement suggesting positive motivation to change. The slash marks are counted, placed in the patient's chart and used to estimate motivation for address the weight/health problem.

The raw data for the three variables is provided in Table 1.

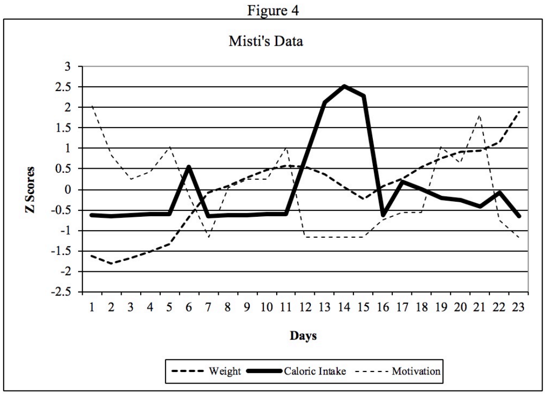
Table 1

Day	Weight	Caloric Intake	Motivation
1	85.6	2010	16
2	84.7	1993	10
3	85.3	2002	7
4	86.1	2011	8
5	86.9	2015	11
6	90.1	2641	5
7	93.1	1996	0
8	93.9	1998	6
9	94.8	2005	7
10	95.7	2015	7
11	96.3	2021	11
12	96.1	2746	0
13	95.2	3482	0
14	93.7	3682	0
15	92.3	3563	0
16	93.9	2003	2
17	94.7	2435	3
18	96.1	2344	3
19	97.1	2221	11
20	97.9	2201	9
21	98.1	2119	15
22	99.1	2301	2
23	102.6	1992	0

In order to be coherently compared, the data needs to be transformed to a common metric. Z-score transformation is ideally suited for this objective.

Examining z-scores in Figure 4 enabled the clinical social worker to identify the interrelationship among variables and redirected the clinician's treatment approach. In this case, two clinical issues become immediately apparent because of the z-score transformation.

Figure 4



Z-scores unambiguously demonstrates that Misti had been purging her food. Her food intake had increased by 7-fold, but she continued to lose weight. In addition, three factors become apparent. First, the staff was able to identify the interrelationship among the three variables. This knowledge would assist in reconfiguring the therapeutic intervention. Second, the staff was able to identify the approximate date of the purging. Clinically, they would be able to focus on environmental stimuli that acted as the catalyst. This knowledge and the experience can be used as clinical tool for the production of enhancing a positive outcome. Third, on a macro level, the staff was under the false impression that they had a fail-safe system the prevented patients from purging. Z-score transformation demonstrates that administrators must evaluate and change their policies.

The Method

During the first publication of Bloom and Fischer (1982), the figures employed within this work would take many hours to complete. Today, thousands of data points can be transformed to z-scores and these transformations can be pictured in a chart within 3 to 5 minutes by using Excel®. Unfortunately, the various versions of Excel offer very different procedures to transform raw data to z-scores and then to chart the revised data. Fortunately, for every version of Excel, there exists multiple YouTube videos on how to standardize data, while other videos illustrate how to create a chart. By using YouTube, one can learn how to standardize data within 20 minutes. Learning how to create a chart takes much less time.

A Statistical Issue: t versus z

As a consequence of employing z-scores for the analysis of patterns and trends within a time series analysis, some readers may identify the violation of a statistical assumption. When using the z distribution to test statistical significance, the mathematical eligibility requirements *include knowing* the population mean (signified by the Greek letter Mu – μ) and the population standard deviation (signified by the Greek letter Sigma – σ). These Greek letters are found within the formula used earlier in this paper. In clinical social work practice, it is *extremely rare* for the practitioner to know these two statistical quantities (Moore, Notz & Flinger, 2017). Historically, the z-problem was solved by William S. Gosset (Student, 1908) who found the z-distribution to be problematic for brewing beer and as a result created the t-distribution to address the complex chemical issues. Since that time, social workers have been using the t distribution (rather than the z distribution) to seek statistical significance.

Within this paper, we are not seeking statistical significance, but rather are seeking patterns and trends within a time-series data set. Within this context, there is *no difference* between employing z-scores and t-scores. To demonstrate this fact, data for the Christine Wilder example is reproduced in Figures 5 and 6.

Figure 5, t-scores

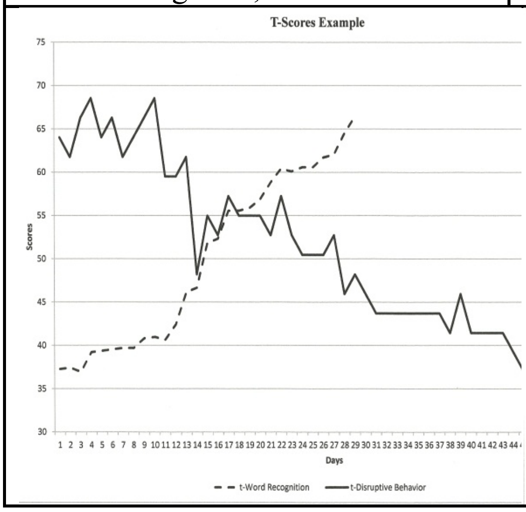
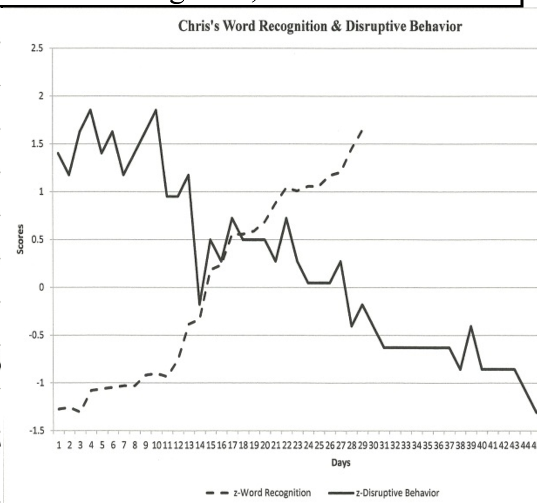


Figure 6, z-scores



In examining the patterns within Figures 5 (t-scores) and 6 (z-scores), one can immediately identify that the patterns are identical. This characteristic is a consequence of the calculus inherent within the production of the t-distribution. Most importantly, all time-series data that has been transformed into t-scores will exhibit the identical pattern and/or trend found in the same data that has been transformed to z-scores. Only one difference will exist between the time-series data; t-scores have a mean of 50, while z-scores have a mean of 0. Since the t and z means are both standardized, the value of the means *has no* importance in this type of analysis.

The question becomes, if using z-scores produces a degree of controversy and there is no difference between z and t, why not use t-scores for analyzing patterns and trends? For practitioners, z-scores are preferred with respect to expense and computation ease. To calculate t-scores on Excel, the practitioner would be required to write the t transformation formula, embed this formula within Excel then calculate all z-scores to insert into the formula. One must calculate the z-scores in order to get the t-scores. Practitioners *need not* be subjected to this meaningless busy work.

Summary and Conclusions

The value of the visual display quantitative information is undisputed (Jacoby, 1998, 1997; Tufte, 2001, 1998, 1997). The employment of z-scores within a graphic illustration enables the clinical social worker to envision the interrelationship among various factors. Our examples demonstrated that z-scores can facilitate our understanding of causal relationships (Chris Wilder), can redirect therapeutic intervention (Mrs. Apple) and can be used to uncover unknown factors such a spurious relationships (Misti).

In the past, the central problem with z-score transformation pertained to excessive time-consumption. Today, virtually every computer has user-friendly spreadsheet software. The authors admit that the first effort to complete a z-score graphic will take longer than 5 minutes. We have learned that the second time is much quicker than the first. By the fourth effort, a person can produce a final draft within three minutes.

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