

Defining Resilience Index Based on Gaussian Distribution

Iara Rosa da Silva¹, Renata Jordani Barbosa^{2,a}, Mariana Aranha de Souza^{3,4}, Ceres Alves de Araújo², & Carlos Alberto Moreira dos Santos¹

¹ Programa de Pós-graduação em Projetos Educacionais de Ciências, Escola de Engenharia de Lorena, Universidade de São Paulo, Lorena - SP, 12.602-810, Brazil

² Programa de Pós-graduação em Psicologia Clínica, Pontifícia Universidade Católica de São Paulo, São Paulo - SP, 05.014-901, Brazil

³ Mestrado Profissional em Educação, Universidade de Taubaté, Taubaté - SP, 12.020-040, Brazil

⁴ Programa de Pós-graduação em Gestão e Desenvolvimento Regional, Centro Universitário do Sul de Minas, Varginha - MG, 37.031-099, Brazil

Correspondence: Carlos Alberto Moreira dos Santos, Programa de Pós-graduação em Projetos Educacionais de Ciências, Escola de Engenharia de Lorena, Universidade de São Paulo, Lorena - SP, 12.602-810, Brazil.

Received: April 18, 2022

Accepted: August 10, 2022

Available online: August 24, 2022

doi:10.11114/ijsss.v10i5.5689

URL: <https://doi.org/10.11114/ijsss.v10i5.5689>

Abstract

This study intends to know whether the Resilience Index established in the Resiliency Scales for Children and Adolescents (RSCA) can be redefined based on Gaussian distribution. Based on qualitative and quantitative analyses, the study was performed using two sets of data obtained with 1268 students, between 9 and 18 years old, enrolled in four schools. The results were discussed statically with the Gaussian distribution. The results provide a precise way to classify the group of students in five different levels of resilience, which are established based on the standard deviation. The results show that the low and high Resilience Index levels represent groups of approximately 16% of the studied population. The possible correlation between the average Resilience Index of a particular school with the Human Development Index, where the school is located, is also discussed.

Keywords: Resilience Index, Gaussian Distribution, RSCA

1. Introduction

Resilience is one of the most important psychological parameters to consider personal strength or weaknesses, and to promote recovering from bad physical or mental events. Several authors have devoted efforts in order to measure resilience over the years (Wagnild & Young 1993; Baruth & Carroll 2002; Connor & Davidson 2003; Friberg *et al.* 2003; Sinclair & Wallston 2004, Harland *et al.* 2005, Campbell-Sills & Stein 2007, Prince-Embury 2007). Nowadays, it is commonly accepted that a person that has higher resilience recovers from a trauma or is more prepared to face problems in the life easier than others (Faye *et al.* 2018). So, estimating resilience of children and adolescents in the schools can be one of the ways to obtain information about possible students' vulnerabilities (Rutter 1987, 1993). Thus, determining resilience in a proper way could have impact on the learning of the students, as well as in their lives (Tugade *et al.* 2004).

Since 2007, Prince-Embury and coworkers (Prince-Embury 2007, 2008, 2009), (Prince-Embury & Saklofske, 2013), (Prince-Embury, Saklofske & Nordstokke, 2016) have devoted many efforts to develop and describe a methodology to determine Resilience Index (*R*) using the so-called Resiliency Scales for Children & Adolescents (RSCA) (Prince-Embury 2007). The methodology is based on the application of a survey composed by three scales related to the "i) Sense of Mastery Scale (MAS) that measures youths' self-perceptions of their skills and competence; ii) Sense of Relatedness Scale (REL) that examines youths' perceived quality of their relationships; and iii) Emotional Reactivity Scale (REA) that assesses how well youth feel about being able to control their emotions" (Prince-Embury 2007). Furthermore, according to Prince-Embury "the scores from these scales can be plotted to create an overall resilience profile that clearly displays youths' strengths and weaknesses" (Prince-Embury 2007).

Foot notes:

^aR. J. Barbosa was Master student at this Institution

In Brazil, this methodology has been validated by Barbosa and de Araújo after applying a survey in three schools of the São Paulo City, in 2008 (Barbosa 2008). The main results and conclusions are very similar to those reported by Prince-Embury (Prince-Embury 2007, 2008).

On the other hand, the importance of the statistical methods for describing many types of data has increased over the years. One of the most important statistical analyses has to do with normal or Gaussian distribution, in which the available data are randomly distributed (Snedecor & Cochran, 1967, Daly *et al.*, 1995). There are many examples reported about that not only in exact and biological sciences, but also in social and human sciences (Limpert, Stahel & Abbt, 2001, Krithikadatta 2014, Altman & Bland, 1995, Sallaberry & Flach, 2019, Livingston, 2004, Daly et al, 1995, Lyon 2014, Nagel 2010, Hebner, 2021). A good example related to the prediction of the human beings' behaviors has to do with elections, in which a survey applied to thousands of people some days before an election can predict the result due to millions of voters (Fortunato 2007, Klimeka *et al.*, 2012, Borghesi & Bouchaud, 2010, Shalders, 2018).

Following similar approach, this work intends to understand whether the Resilience Index defined based on RSCA by Prince-Embury (Prince-Embury 2007) can be well described by the Gaussian distribution.

2. Methodology

Based on quali and quantitative analyses, the study was performed using two sets of data obtained with 1268 students, between 9 and 18 years old, enrolled in four schools, referred in this work as school A to D. Two sets of resilience data were collected using the Resiliency Scales for Children & Adolescents (RSCA) reported in 2007 by Prince-Embury (Prince-Embury 2007) and validated in Brazil one year later (Barbosa 2008). One data set is related to a school located in the interior town of São Paulo state, collected in 2019 (Data set 1 with 42 students), and another is associated with three schools of different districts of the São Paulo city, obtained in 2008 (Barbosa 2008) (Data set 2 with 1226 students).

The data were collected using the sheet forms described in RSCA methodology (Prince-Embury 2007) and available in the reference (Barbosa 2008), which were filled up by the students within 20 to 30 minutes, under supervision of the students' teachers and some of these authors, during break times established between classes. Participation of the students in the surveys was allowed only after the consent form agreement by one of the student's parents. The numbers of students, their age and genders, and details about the type of the schools are shown in the Table 1.

Table 1. Age, genders (F = female and M = male), and numbers of students of each school are shown. The type of the school is also reported

School	A		B		C		D	
Type	Confessional		State		Town		Town	
Age	F	M	F	M	F	M	F	M
9	7	1	-	-	36	36	-	-
10	4	5	1	2	48	59	-	-
11	3	9	18	6	46	42	20	24
12	7	3	22	18	36	52	17	20
13	-	2	37	20	34	45	2	2
14	-	1	28	14	44	40	20	35
15	-	-	29	23	11	19	34	24
16	-	-	27	30	2	1	26	51
17	-	-	29	30	-	1	17	22
18	-	-	12	13	-	-	-	1
Total	21	21	203	156	257	295	136	179
	42		359		552		315	
%	50	50	57	43	47	53	43	57

Both data set are analyzed in a similar way to that reported for the RSCA (Prince-Embury 2007), which is based on a survey with 64 questions, available in reference (Barbosa 2007). The answer for each question uses a Likert scale with 5 levels, from zero up to 4, which corresponds from never to always, respectively. Instead using the absolute score for each scale, we have used the average of each one, which varied from 0 up to 4.

The level of consistency of each data set was established using the Cronbach's alpha coefficient (Perterson 1994, Streiner 2003, Tavakol & Dennick, 2011) by comparing the obtained values with that reported previously by Prince-Embury (Prince-Embury 2007).

Furthermore, the data are discussed on the basis of the Gaussian distribution statistics (Snedecor & Cochran, 1967, Daly *et al.*, 1995). The statistical analysis was first tested using the answers by 42 students of the School A and finally applied to the survey performed with 1226 students of the Schools B, C, and D.

The results show that is possible to describe the data of the four schools with the Gaussian distribution in very good way, which allowed us to precisely define intervals of Resilience Index based on the standard deviation, as well as to directly

correlate the profile of the schools and the community around them with the average Resilience Index of the students of a particular school.

3. Results and Discussion

Table 2 compares the Cronbach’s alpha coefficients for the data by Prince-Embury (2007) with those obtained in this work for each scale.

Table 2. Cronbach’s alpha coefficients of the three scales for the data by Prince-Embury (Prince-Embury 2007) and both data sets of this work

Scale	Data by Prince-Embury			
	Child (9 to 11)	Adolescents	Data set 1	Data set 2
MAS	0.85	0.95	0.80	0.83
REL	0.89	0.95	0.92	0.90
REA	0.90	0.94	0.86	0.87

The coefficients are smaller for the data sets of this work in comparison with that of the previous one, especially for the group adolescent, but they are still with good internal consistency (Prince-Embury 2007, Barbosa 2008). Although the data sets 1 and 2 were collected in different moments, more than 10 years apart, the very close values suggest that any statistical analysis probably will provide similar results.

Thus, both data sets were analyzed by calculating the averages and the standard deviations. Table 3 shows the averages and correspondent standard deviations (Snedecor & Cochran, 1967, Daly et al, 1995) of each scale (MAS, REL, and REA) (Prince-Embury 2007, Barbosa 2008) and the Resilience Index (*R*), which was calculated after averaging the Resilience Index of all students.

Table 3. Averages for the three scales and Resilience Index with the correspondent standard deviations

Data Set	School	# of students	MAS	REL	REA	<i>R</i>
1	A	42	2.56 ± 0.55	2.70 ± 0.64	2.50 ± 0.60	2.59 ± 0.47
2	B, C, and D	1226	2.67 ± 0.49	2.77 ± 0.63	2.48 ± 0.67	2.64 ± 0.45

It is possible to observe that the averages in all subscales range from 2.48 up to 2.77, and the standard deviations vary from 0.49 to 0.67. Furthermore, it is interesting to notice that the average of each scale and the Resiliency Index are closed in both data sets, in agreement to the expected by the Cronbach’s alpha coefficients shown in Table 2.

In Figure 1 is displayed the Resilience Index of each student for both data sets.

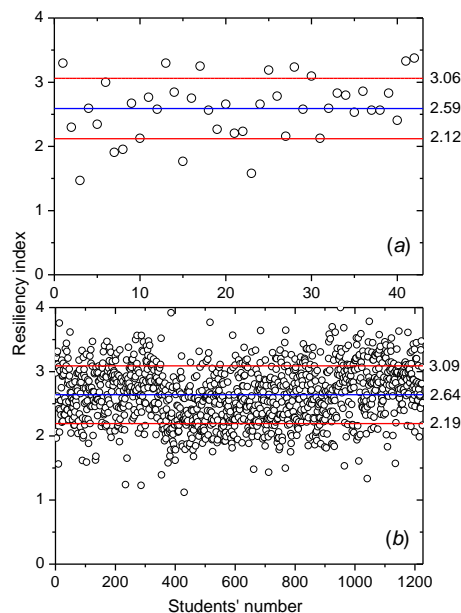


Figure 1. Resilience Index of each student for the (a) data set 1 (N = 42) and (b) data set 2 (N = 1226). The numbers at the right side indicate the average Resilience Index with the correspondent standard deviation for each data set (see Table 3 again)

Horizontal lines mark the averages (blue lines) and the values for one standard deviation above and below it (red lines). It is clear that most of the students’ Resilience Indexes in both data sets are around the average and only a small fraction of students are above and below the $\bar{R} \pm \sigma$ values, respectively.

The results shown in Table 3 and Figure 1 strongly suggest that each data set can be properly described by the Gaussian distribution. Figure 2 displays the occurrence (or frequency) of the Resilience Index of each student in intervals defined by the simplest way, *i. e.* the square root choice (Nuzzo 2019, Fushimi *et al.*, 2019), which provides $\sqrt{42} \sim 6$ and the $\sqrt{1226} \sim 35$ intervals for the data set 1 and 2, respectively.

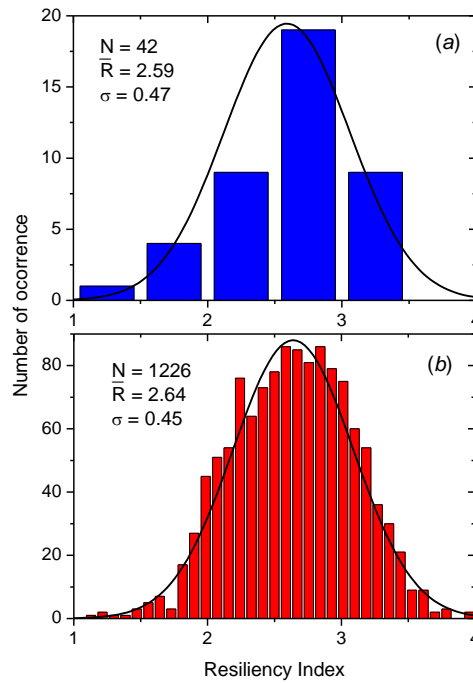


Figure 2. Gaussian distributions of the number of occurrences for (a) data set 1 (6 intervals) and (b) data set 1 (35 intervals). The data set 2 fits the Gaussian distribution better than the data set 1 because of the number of students in each data set.

The full lines represent the Gaussian distribution given by (Snedecor & Cochran, 1967, Daly *et al.*, 1995).

$$f(R) = f(\bar{R}) e^{-\frac{1}{2} \left(\frac{R - \bar{R}}{\sigma} \right)^2}, \quad (1)$$

using the averages (\bar{R}) and the standard deviations (σ) given in the last column of the Table 3 for each data set, taking pre-factors $f(\bar{R})$ defined arbitrarily, since they have no impact on the percentage distribution within the ranges.

In spite of the schools' profiles represented by their type and location, average of ages, gender distribution, number of students, and the year of data collection, both data sets show good fitting with regard to the normal distribution, which confirms the randomly distribution expected for data described by the Gaussian statistics. This is important because one can use it to predict the fractions of Resilience Index of a population of students without to take into account any detail of a particular student in that population. Thus, we explore the consequences of this observation. The first of them is to establish some precise ranges for the Resilience Index, which can be related to its average and the standard deviation. Based on the results in the last column of the Table 3 and Figures 1 and 2 we define the ranges using the standard Resilience Index as 2.6 ± 0.5 . For such a case, we are able to plot the schematic Gaussian distribution in Figure 3, in which 5 ranges can be defined based on $\pm \sigma/2$ intervals with population fractions calculated by making the integration of the Equation (1) between the lower and upper limits of each range (Daly *et al.*, 1995, Grami 2020). Table 4 classifies the limits of each range.

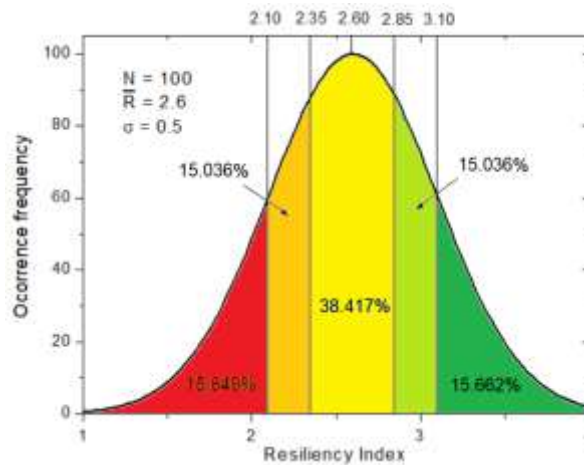


Figure 3. Schematic Gaussian distribution divided into 5 Resilience Index ranges. Each range has the expected percentage shown. The number of students in the distribution is assumed to be 100

Table 4. Ranges defined from the Gaussian distribution shown in Figure 3. The ranges are related to the half of the standard deviation, *i. e.* $\sigma/2 = 0.25$. The last column shows the fraction of the population expected to be in each correspondent range

Classification	Range		% population
High	$R > \bar{R} + \sigma$	$R > 3.10$	15.662
Above average	$\bar{R} + \sigma/2 \leq R \leq \bar{R} + \sigma$	$2.85 \leq R \leq 3.10$	15.036
Average	$\bar{R} - \sigma/2 < R < \bar{R} + \sigma/2$	$2.35 < R < 2.85$	38.417
Below average	$\bar{R} - \sigma \leq R \leq \bar{R} - \sigma/2$	$2.10 \leq R \leq 2.35$	15.036
Low	$R < \bar{R} - \sigma$	$R < 2.10$	15.849

The difference between the percentages in the lower (15.662%) and higher (15.849%) ranges has to do with small dislocation of the distribution from the center to the right, which should be ideally at $\bar{R} = 2.5$, the middle point between 1 and 4.

Interesting is to notice that one is able to see the expected standard distribution of a group of students of a particular classroom or a school. Based on the normal distribution predicted here, near 16% of a population should have low Resilience Index, which should be the first group to receive psychological attention with regard to the other ones.

Based on the new ranges defined in this work, Table 5 compares the absolute score, reported previously by Prince-Embury (Prince-Embury 2007), with those shown in Table 4 by multiplying R by $80/4$, the absolute score over the maximum average score.

Table 5. Comparison of the ranges defined based on the absolute score, reported by Prince-Embury, with those calculated from the Gaussian distribution given in Table 4

Classification	Total score by Prince-Embury	Total score in this work
High	$R \geq 60$	$R > 62$
Above average	$56 \leq R \leq 59$	$57 \leq R \leq 62$
Average	$46 \leq R \leq 55$	$47 < R < 57$
Below average	$41 \leq R \leq 45$	$42 \leq R \leq 47$
Low	$R \leq 40$	$R < 42$

Although there are some similarities between the two scores, there are also three important differences in the ranges proposed in this work, as follow: the total score i) is defined based on a statistical basis, *i. e.* the Gaussian distribution; ii) defines the average Resilience Index in a continuous way; and iii) avoids the problem with the scale REL, which has a total score of 96 compared to the 80 of the MAS and REA (Prince-Embury 2007, 2008; Barbosa 2008).

Once we have the expected values for each range, we can analyze the data of each school in separated way. Table 6 shows MAS, REL, REA, and R values for the four schools.

Table 6. MAS, REL, REA, and R values for the schools A to D.

School	# of Students	MAS	REL	REA	R
A	42	2.56 ± 0.55	2.70 ± 0.64	2.50 ± 0.60	2.59 ± 0.47
B	359	2.71 ± 0.49	2.78 ± 0.56	2.65 ± 0.65	2.71 ± 0.42
C	552	2.52 ± 0.53	2.53 ± 0.60	2.40 ± 0.67	2.48 ± 0.42
D	315	2.87 ± 0.53	3.16 ± 0.55	2.44 ± 0.66	2.82 ± 0.43

Although the deviations impose overlap between the average values, it is possible to draw some important observations. For instance, school D has $REL = 3.16 \pm 0.55$ which is well above other schools, especially compared to the school C (2.53 ± 0.60). Furthermore, school D has $R = 2.82 \pm 0.43$ which is higher than that of the expected score (2.6 ± 0.5), while school C has lower Resilience Index (2.48 ± 0.42).

These differences are now discussed. Table 7 shows the percentage of the students' population separated in the five ranges.

Table 7. Fraction of the students' population of each school separated into five ranges. The column "All schools" is calculated based on the weighted average using the number of students in each school (see Table 1) and the percentage of the population in each range. The last two columns compare the average in the five ranges with that expected by the Gaussian distribution.

Range	School / % Population				All schools	Expected
	A	B	C	D		
$R > 3.10$	16.67	16.71	9.06	26.67	15.85	15.662
$2.85 \leq R \leq 3.10$	7.14	23.96	10.87	23.49	17.59	15.036
$2.35 < R < 2.85$	45.24	40.39	37.50	36.19	38.25	38.417
$2.10 \leq R \leq 2.35$	19.05	11.42	23.01	7.30	15.69	15.036
$R < 2.10$	11.90	7.52	19.57	6.35	12.62	15.849

The comparison of the last two columns shows that the averages for all schools are very close to the expected by the normal distribution. This is a consequence of the randomly distribution expected in the Gaussian statistics. On the other hand, there are also some important deviations from the expected values in each range for the schools, which are listed below:

i) school A has an increase of the intermediate range as consequence of the lower fraction in second range, suggesting a tendency to have more students with lower resilience than expected;

ii) school B has lower fraction of students in the two lowest ranges, which are compensated by a significant increase of the upper ranges, providing a higher Resilience Index in this school;

iii) school C tends to have more students with lower Resilience Index, since the two lower and two higher limits are above and below the expected fractions, respectively; and

iv) in opposite direction of the school C, school D has a clear dislocation of the distribution from the two lower limits to the two upper limits, supporting the idea that the students in this school are much more resilient than the others.

Finally, the different fractions of the three scales and R must be related to the profile of the students in each school. During the course of this work, we have noticed that this could be related to the socio economical aspects of the community around the schools. So, we decide to briefly compares the Human Development Index (HDI) of the district or town where the school is (PNUD, 2013) with the Resilience Index of each one. Schools B and D are at locations which have high HDI (0.957 and 0.961, respectively) and have higher R compared to the expected value. On the other hand, school C, which has the lowest R , is in a place where the HDI is lower (0.884) than the schools B and D. Drawing this correlation to the school A (HDI = 0.794) is more difficulty, although it shows a smaller fraction in the second range compared to the expected value. This possible relationship between the community around the school and its Resilience index must be addressed in future.

4. Conclusion

The Resilience Index established is RSCA is redefined within the Gaussian distribution statistics. This allowed to define the limits of the five resilience ranges based on the standard deviations in a precise way.

Taking the data for the four schools together is possible to show that, in spite the schools' and students' profiles, the average of the fractional population in each range is very close to the expected values, showing that the data follows a randomly distribution.

The analysis of the data for each school shows some important differences in the fractions of the population with regard to those expected. Some schools have higher Resilience Index compared to others.

The results suggest a possible relationship between the socio economic development of the region where the school is and the average Resilience Index of the students. The statistical analyses reported here defines a simple and precise way to compare the Resilience Index of different students and different schools.

References

- Altman, D., & Bland, J. M. (1995). Statistics notes: the normal distribution. *BMJ*, *310*, 298. <https://doi.org/10.1136/bmj.310.6975.298>
- Barbosa, R. J. (2008). *Tradução e validação da escala de resiliência para crianças e adolescentes de Sandra Prince-Embury*. [Translation and validation of the Sandra Prince-Embury resilience scale for children and adolescents]. Dissertação de mestrado apresentada ao Núcleo de psicossomática e psicologia hospitalar do Programa de estudos pós-graduados em psicologia clínica da PUCSP. São Paulo, 2008.
- Baruth, K. E., & Carroll, J. J. (2002). A formal assessment of resilience: the Baruth Protective Factors Inventory. *The Journal of Individual Psychology*, *58*, 235-244. Retrieved from <https://psycnet.apa.org/record/2002-04435-004>
- Borghesi, C., & Bouchaud, J. P. (2010). Spatial correlations in vote statistics: a diffusive field model for decision-making. *The European Physical Journal B*, *75*, 395-404. <https://doi.org/10.1140/epjb/e2010-00151-1>
- Campbell-Sills, L., & Stein, M. B. (2007). Psychometric analysis and refinement of the Connor–Davidson resilience scale (CD-RISC): Validation of a 10-item measure of resilience. *Journal of Traumatic Stress: Official Publication of the International Society for Traumatic Stress Studies*, *20*(6), 1019-1028. <https://doi.org/10.1002/jts.20271>
- Connor, K. M., & Davidson, J. R. (2003). Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). *Depression and anxiety*, *18*(2), 76-82. <https://doi.org/10.1002/da.10113>
- Daly, F., Hand, D. J., Jones, M. C., Lunn, A. D., & McConway, K. J. (2010). *Elements of Statistics*, Pearson Education Limited (1th ed. 1995). (Chapters 2 and 5). Retrieved November 10, 2021, from <https://www.open.edu/openlearncreate/mod/oucontent/view.php?id=18263§ion=1.2.1>
- Faye, C., McGowan, J. C., Denny, C. A., & David, D. J. (2018). Neurobiological mechanisms of stress resilience and implications for the aged population. *Current neuropharmacology*, *16*(3), 234-270. <https://doi.org/10.2174/1570159X15666170818095105>
- Fortunato, S., & Castellano, C. (2007). Scaling and Universality in Proportional Elections. *Physical Review Letters*, *99*, 138701. Retrieved from <https://doi.org/10.1103/PhysRevLett.99.138701>
- Friborg, O., Hjermadal, O., Rosenvinge, J. H., & Martinussen, M. (2003). A new rating scale for adult resilience: what are the central protective resources behind healthy adjustment? *International Journal of Methods in Psychiatric Research*, *12*(2), 65-76. <https://doi.org/10.1002/mpr.143>
- Fushimi, T., Iwasaki, K., Okubo, S., & Saito, K. (2019). Construction of Histogram with Variable Bin-Width Based on Change Point Detection. *Springer Nature Switzerland AG*. P. Kralj Novak et al. (Eds.), LNAI 11828 (pp. 40-50). https://doi.org/10.1007/978-3-030-33778-0_4
- Grami, A. (2020). *Probability, Random Variables, Statistics, and Random Processes Fundamentals & Applications*. (Chapter 7 The Gaussian Distribution). John Wiley & Sons, Inc. <https://doi.org/10.1002/9781119300847.ch8>
- Harland, L., Harrison, W., Jones, J. R., & Reiter-Palmon, R. (2005). Leadership behaviors and subordinate resilience. *Journal of Leadership & Organizational Studies*, *11*(2), 2-14. <https://doi.org/10.1177/107179190501100202>
- Klimeka, P., Yegorovb, Y., Hanela, R., & Thurner, S. (2012). Statistical detection of systematic election irregularities. *PNAS*, *109*(41), 16469-16473. Retrieved from www.pnas.org/cgi/doi/10.1073/pnas.1210722109
- Krithikadatta, J. (2014). Statistics Simplified - Normal Distribution. *Journal of Conservative Dentistry*, *17*(1), 96-97. <https://doi.org/10.4103/0972-0707.124171>
- Limpert, E., Stahel, W. A., & Abbt, M. (2001). Log-normal Distributions across the Sciences: Keys and Clues. *BioScience*, *51*(5), 341. [https://doi.org/10.1641/0006-3568\(2001\)051\[0341:LNDATS\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2001)051[0341:LNDATS]2.0.CO;2)
- Livingston, E. H. (2004). The Mean and Standard Deviation: What Does It All Mean? *Journal of Surgical Research*, *119*(2), 117-123. <https://doi.org/10.1016/j.jss.2004.02.008>
- Lyon, A. (2014). Why are Normal Distributions Normal? *The British Journal of Philosophy of Science*, *65*(3), 621-649. <https://doi.org/10.1093/bjps/axs046>
- Nagel, M. (2010). A Mathematical Model of Democratic Elections. *Current Research Journal of Social Sciences*, *2*(4), 255-261. Retrieved October 5, 2021, from <https://emilkirkegaard.dk/en/wp-content/uploads/A-Mathematical-Model-of-Democratic-Elections.pdf>

- Nuzzo, R. L. (2019). Histograms: A Useful Data Analysis Visualization, *PM R*, 11, 309-312. Retrieved June 10, 2021, from <https://onlinelibrary.wiley.com/doi/epdf/10.1002/pmrj.12145>
- Perterson, R. A. (1994). A Meta-Analysis of Cronbach's Coefficient Alpha. *Journal of Consumer Research*, 21(2), 381-391. <https://doi.org/10.1086/209405>
- PNUD Programa das Nações Unidas para o Desenvolvimento (2013). *Índice de Desenvolvimento Humano*. IDM Municípios 2010. Retrieved January 10, 2022, from <https://www.br.undp.org/content/brazil/pt/home/idh0/rankings/idhm-municipios-2010.html>
- Prince-Embury, S. (2007). Resiliency Scales for Children and Adolescents: A Profile of Personal Strengths. *Canadian Journal of School Psychology*, 22(2), 255-261. <https://doi.org/10.1177/0829573507305520>
- Prince-Embury, S. (2008). The Resiliency Scales for Children and Adolescents, Psychological Symptoms, and Clinical Status in Adolescents. *Canadian Journal of School Psychology*, 23(1), 41-56. <https://doi.org/10.1177/0829573508316592>
- Prince-Embury, S. (2009). The Resiliency Scales for Children and Adolescents as Related to Parent Education Level and Race/Ethnicity in Children. *Canadian Journal of School Psychology*, 24(2), 167-182. <https://doi.org/10.1177/0829573509335475>
- Prince-Embury, S., & Saklofske, D. H. (Eds.). (2013). Resilience in Children, Adolescents, and Adults: translating research into practice. *The Springer Series on Human Exceptionality*. Springer, New York, NY. <https://doi.org/10.1007/978-1-4614-4939-3>
- Prince-Embury, S., & Saklofske, D. H., & Nordstokke, D. W. (2016). The Resiliency Scale for Young Adults. *Journal of Psychoeducational Assessment*, 1-15. <https://doi.org/10.1177/0734282916641866>
- Hebner, M., Dahlin, J., Poissant, P., & Brunson, J., *Galton Board: Examples of Normal Distribution and Probability in Every Day Life*. Four Pines Publishing Inc. Retrieved December 15, 2021, from <https://galtonboard.com/probabilityexamplesinlife>
- Rutter, M. (1987). Psychosocial resilience and protective mechanisms. *American journal of orthopsychiatry*, 57(3), 316-331. <https://doi.org/10.1111/j.1939-0025.1987.tb03541.x>
- Rutter, M. (1993). Resilience: some conceptual considerations. *Journal of adolescent health*, 14(8), 626-631. [https://doi.org/10.1016/1054-139X\(93\)90196-V/](https://doi.org/10.1016/1054-139X(93)90196-V/)
- Sallaberry, J. D., & Flach, L. (2019). Contemporary Economic Determinants for the Choice of the Leaders of the Brazilian Public Administration. *Revista Eletrônica de Administração – REAd, Porto Alegre*, 25(2), 119-149. <https://doi.org/10.1590/1413-2311.242.89611>
- Shalders, A. (2018). *Como funcionam as pesquisas eleitorais?* Retrieved January 6, 2022, from <https://www.bbc.com/portuguese/brasil-43845326>
- Sinclair, V. G., & Wallston, K. A. (2004). The development and psychometric evaluation of the Brief Resilient Coping Scale. *Assessment*, 11(1), 94-101. <https://doi.org/10.1177/1073191103258144>
- Snedecor, G. W., & Cochran, W. G. (1967). *Statistical Methods* (6th ed). Ames: Iowa State University Press (Chapter 2). ISBN-10: 0813815614.
- Streiner, D. L. (2003). Starting at the Beginning: An Introduction to Coefficient Alpha an Internal Consistency. *JOURNAL OF PERSONALITY ASSESSMENT*, 80(1), 99-103. https://doi.org/10.1207/S15327752JPA8001_18
- Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2, 53-55. <https://doi.org/10.5116/ijme.4dfb.8dfd>
- Tugade, M. M., Fredrickson, B. L., & Feldman Barrett, L. (2004). Psychological resilience and positive emotional granularity: Examining the benefits of positive emotions on coping and health. *Journal of personality*, 72(6), 1161-1190. <https://doi.org/10.1111/j.1467-6494.2004.00294.x>
- Wagnild, G. M., & Young, H. M. (1993). Development and psychometric evaluation of the Resilience Scale. *Journal of Nursing Measurement*, 1(2), 165-178. Retrieved from <https://pubmed.ncbi.nlm.nih.gov/7850498>

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the [Creative Commons Attribution license](https://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.