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Examining the role of gesture to web-based Mathematics instruction for Adults

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Abstract

Investigating the effectiveness of gestures in enhancing adult education, particularly in the comprehension of complex statistical concepts like standard deviation, is crucial in educational setting. This study examines the impact of instructor gestures within both algorithmic and conceptual teaching frameworks, assessing how these non-verbal cues improve understanding and problem-solving skills among adult learners. The research employed a linear mixed-effects model to analyze the effects of different instructional conditions (with or without gesture) on participants' performance scores. The model included math anxiety and prior knowledge as covariates to account for individuals. The results indicated that incorporating gestures into instruction consistently improved learning outcomes across both algorithmic and conceptual methods. However, no significant differences were found between these instructional methods in terms of overall effectiveness. This study underscores the potential of multimodal teaching strategies, recommending the inclusion of gestures in teaching complex subjects like statistics to foster a deeper understanding and retention of material.

Gestures, a universal form of non-verbal communication, are used across all cultures and ages to convey information and enhance verbal communication (Iverson & Goldin-Meadow, 1998). In educational settings, teachers frequently produce gestures when they instruct children. As children absorb knowledge, they are more likely to incorporate gestures and perform better in post-test when they observe teachers using gestures (Cook & Goldin-Meadow, 2006). Previous research has found spoken instruction presented with gesture promotes learning better than the same spoken instruction presented without gesture (Church et al., 2004). This suggests that gestures could play a crucial role in teaching complex concepts, particularly those that students traditionally find challenging.

Given the potential of gestures to enhance learning, this study explores their impact within the context of teaching standard deviation— a statistical measure that quantifies the amount of variation or dispersion of a set of data values. This concept is fundamental to understanding statistical distributions but is known for its difficulty among both learners and teachers (Chan & Ismail, 2013; Huey et al., 2018). This makes standard deviation an ideal case for examining how gestural teaching can improve comprehension and problem-solving skills. This study, therefore, investigates the role of instructor gestures in enhancing adults' comprehension and problem-solving skills in standard deviation, focusing on both algorithmic and conceptual instructional approaches.

The impacts of gesture on learning can be examined within the frameworks of algorithmic and conceptual instruction. Algorithmic instruction, which focuses on teaching formulas and procedures, emphasizes the ability to follow specific steps and apply formulaic knowledge efficiently. In contrast, conceptual instruction, which emphasizes understanding underlying principles, requires learners to grasp and apply abstract principles and develop a deeper comprehension of the material. Nurrenbern and Pickering (1987) found that university students performed better on computational questions than on conceptual ones. This disparity suggests that students might predominantly engage in rote learning methods, which emphasize memorization and algorithmic problem-solving, rather than in deeper conceptual learning approaches that require understanding and applying underlying principles. On the other hand, conceptual learning often applies definitions and principles that enable individuals to understand new knowledge (Engelbrecht et al., 2005). Papaphotis and Tsaparlis (2008) noted that competence in algorithmic learning might be independent of competence in conceptual questions, indicating that different cognitive processes or skills might be involved in these two types of learning.

This distinction between algorithmic and conceptual learning sets the stage for exploring how gestures can enhance learning in these different contexts. Gestures introduce a unique visual and spatial dimension to verbal communication (Kendon, 1980). When gesture is produced simultaneously with speech, it allows speakers to present visual information simultaneously with words, reinforcing the spoken message (Singer & Goldin-Meadow, 2005). This dual presentation of speech and gesture was evidenced in a study by Valenzeno et al. (2003), where children showed better performance in understanding symmetry after viewing lessons that incorporated both speech and gesture compared to lessons with only speech. Moreover, gestures can significantly enhance learning, particularly when they are used as complementary strategies alongside verbal instruction (Singer & Goldin-Meadow, 2005). While teaching multiple problem-solving strategies solely through speech can be less effective, incorporating a second strategy through gestures enhances learning outcomes (Singer & Goldin-Meadow, 2005). This suggests that presenting multiple strategies can be beneficial, but the manner of presentation (speech vs. gesture) matters significantly (Singer & Goldin-Meadow, 2005).

The question then arises: why is gesture beneficial for learning? Research has shown that using gestures during instruction offers distinct advantages, particularly in the teaching of complex algorithms to children. Singer and Goldin-Meadow (2005) highlight that when algorithms are taught solely through verbal instructions, the core concepts they are meant to support may be overshadowed. In contrast, presenting algorithms through gestures facilitates a clear, step-by-step process that avoids making children overly reliant on rote procedures. This benefit likely arises because gestures, being less direct than speech, present information in a manner that is less overwhelming, allowing learners to engage with the material more fully and effectively (Singer & Goldin-Meadow, 2005).

This benefit of gestures has been well-documented in children's learning, especially in how they grasp the relationship between principles and algorithms. It allows for the simultaneous presentation of both the principle and the algorithm which highlight the relationship between them, unlike speech which typically presents them one after the other (Singer & Goldin-Meadow, 2005). Rather than combining conceptual and algorithmic instructional elements, our study specifically aligns the type of gestures with the corresponding speech content. Conceptual gestures accompany conceptual explanations to enhance understanding of underlying principles, while algorithmic gestures are paired with algorithmic speech to clarify step-by-step procedures. While much of the existing research on the educational benefits of gestures focuses on children, it could potentially represent a broader phenomenon in concept acquisition across the lifespan. Nonetheless, our understanding of how gestures impact adult learning, especially in mathematical contexts like understanding standard deviation, remains underexplored.

Understanding the impact of gestures on learning outcomes necessitates a closer look at other underlying factors that might influence these instructional strategies. Specifically, math anxiety is a critical factor known to influence cognitive functions. Research has demonstrated that math anxiety can occupy essential working memory resources, crucial for processing new information and solving complex problems (Ashcraft & Kirk, 2001). This effect on cognitive resources is a primary reason for including math anxiety as a random effect in our study—to control for its potential confounding influence on the dependent variable, which is the improvement in performance scores.

Similarly, prior knowledge plays an essential role in how learners process and integrate new information. Learners with a strong base in relevant knowledge areas can assimilate new information more effectively (Bransford & Johnson, 1972). By treating prior knowledge as a random effect, we aim to understand how varying levels of pre-existing knowledge influence the effectiveness of gesture-integrated instructional methods.

Current Study

The current study delves into how gestures can enhance the learning of standard deviation by comparing their effectiveness in two instructional contexts: algorithmic, where gestures may accompany formulas and procedural explanations, and conceptual, where they might illustrate spatial and abstract aspects of the concept. By examining how gestures integrate into these instructional approaches, the research aims to provide insights into how such non-verbal cues can improve adults' understanding of standard deviation. Additionally, the research examines whether the impact of gestures is consistent across both instructional methods. In other words, whether the nature of the instruction influences the effectiveness of gestural enhancements in teaching standard deviation.

The study is using participants' difference between participants' and post on problems about the mean and standard deviation as the dependent variable – the use of gestures and the type of instruction (algorithmic vs. conceptual) – resulting in four distinct versions of instructional approaches. These versions are: 1) algorithmic instruction with gestures, 2) algorithmic instruction without gestures, 3) conceptual instruction with gestures, and 4) conceptual instruction without gestures. We hypothesize that conceptual instruction with the use of gestures can enhance participants' performance score of standard deviation the most, meaning fostering conceptual knowledge with the help of gestures could have the most effect on helping adults understand standard deviation. We predicted the presence of gestures aids learning by reducing learners' cognitive load.

Alternatively, algorithmic instruction without gestures could result in better performance. Although only teaching formulas lack a deeper understanding of mathematical concepts (Givvin et al., 2009), people might find formulas straightforward, and gestures could potentially distract learning. The effectiveness of algorithmic versus conceptual instruction may vary for several reasons. Given that algorithmic instruction primarily involves teaching formulas, its effectiveness could be attributed to the straightforward and direct nature of this approach. Whereas a conceptual focus may enhance knowledge transfer by providing a deeper understanding of underlying principles.

Method

Participants

The study recruited 250 adults aged 18 years and older through Prolific, an online platform where participants voluntarily sign up to complete studies. Participants were compensated for their time and effort. 41 participants held a Bachelor's degree. 24 participants with a Graduate degree and 22 with at least one year of college education. Additionally, 20 participants had completed high school. 14 with a 2-year undergraduate degree, 2 with a trade license or certificate, and 1 with some graduate training but no degree completion. The majority of participants identified as White ($n = 72$), followed by African American ($n = 26$) and Asian ($n = 11$). The sample also included participants who identified as Mixed ($n = 8$) and Hispanic ($n = 5$).

Math anxiety was assessed using a self-reported Likert scale, with scores ranging from 1 to 5. The mean math anxiety score was 3.22 ($SD = 1.41$). Analysis revealed a significant negative correlation between math anxiety and total performance scores (sum of pretest and posttest scores), $r(248) = -0.31$, $p < .05$, indicating that higher math anxiety was associated with lower performance in understanding standard deviation.

Materials and Design

Instructional materials were designed for this study to teach the concept of standard deviation, incorporating both algorithmic and conceptual teaching strategies with and without the use of gestures. We created a series of instructional videos in which a female native English-speaking instructor teaches the content standing beside a histogram. Each version was tailored to one of the four experimental conditions: Conceptual Learning with Gestures, Conceptual Learning without Gestures, Algorithmic Learning with Gestures, and Algorithmic Learning without Gestures (See Appendix for example for video format and verbal instructions). The example of verbal instructions These videos were hosted on the Qualtrics platform. In order to maintain high attentiveness and data integrity, attention check questions were randomly embedded within both the pretest and posttest. Participants who failed these attention checks were excluded from the analysis. 24 of them failed the attention check.

Procedure

All participants initially watched a short instructional video designed to familiarize them with the basic concepts of interpreting histograms, in which no gestures were used, and the instructor was not visible. This was followed by a pretest consisting of six questions on standard deviation and mean, where participants were asked to explain their answers. For example, one question posed to participants was: “Imagine that you add 5 data points to the dataset. They all have the same value as the mean. Given that the original mean is 7, will the mean change? Will the standard deviation change?” This allows us to assess their understanding and categorize their prior knowledge as either above-average or below-average based on their performance.

After completing the pretest, participants viewed the instructional video corresponding to their randomly assigned condition. Following the video, they completed a set of six posttest questions that mirrored the pretest, designed to measure any changes in understanding or performance. After completing the posttest, participants were asked to fill out a Likert-scale questionnaire and their subjective experiences and attitudes towards the tasks they had completed. This questionnaire included statements such as “The task was difficult for me”, “I was focused during this task”, and “I understand the way standard deviation is used in this study”, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). Additionally, items on the questionnaire addressed participants' confidence in their answers, their general anxiety about mathematics, and their overall self-assessment of mathematical competence. Participants' demographic information including ethnicity, gender, and educational background was collected post-experiment.

Result

A linear mixed-effects model was employed using the 'lme4' package in R. This model analyzed the effects of various instructional conditions on learners' performance improvements, while controlling for individual variability in math anxiety and pretest knowledge levels. The algorithmic instruction without gestures served as the baseline condition. The dependent variable was the change in performance scores from pretest to posttest across conditions. In conditions involving gestures, participants in the Algorithmic instruction group showed a mean score increase of 0.54 (SD = 2.01), while those in the Conceptual instruction group demonstrated a slightly higher increase of 0.63 (SD = 1.98). In contrast, participants without gesture support exhibited smaller improvements; those in the Algorithmic condition had a mean decrease of -0.26 (SD = 1.93), and those in the Conceptual condition showed a modest increase of 0.21 (SD = 1.91). The variables of math anxiety (M=3.22, SD = 1.41) and prior knowledge were treated as random effects to understand the variability in score improvements among participants.

Fixed effects

The fixed effects analysis showed the differential impacts of various instructional conditions on learners' performance increases in comparison to different conditions. Notably, "Algorithms with Gestures" significantly enhanced performance compared to the algorithmic condition without Gesture (b = 0.84, SE = 0.36, t (220.90) = 2.34, *p* = .020). "Conceptual Instruction with Gestures" also significantly improved performance (b = 0.88, SE = 0.35, t (220.08) = 2.51, *p* = .013). Conversely, "Algorithms without Gestures" did not show a statistically significant impact on performance (b = -0.39, SE = 0.73, t (1.75) = -0.54, *p* = .65). Likewise, "conceptual Instruction without Gestures" did not show a statistically significant difference from the baseline (b = 0.41, SE = 0.35, t(220.00) = 1.20, *p* = .23).

Random effects

The analysis of random effects revealed variations in score increases among participants. The variance component for Math Anxiety was 0.204 with a standard deviation of 0.452, indicating a moderate level of variability associated with this factor. Similarly, the Pretest Binary condition showed a variance of 0.731 and a standard deviation of 0.86, suggesting a higher but still moderate level of variability due to initial knowledge levels. While these values point to individual differences in response to the instructional conditions, neither variance component approaches the magnitude of the residual variance (3.42 with a standard deviation of 1.85), which dominates the model. This indicates that other unaccounted factors might play a more significant role in influencing score increases.

Likelihood Ratio Test

The inclusion of Math Anxiety as a random effect in the model was evaluated using a Likelihood Ratio Test. While the addition of this effect did not result in a statistically significant improvement at the traditional 0.05 level ($\chi^2 = 3.76$, df = 1, $p = 0.05245$), it indicated a marginal improvement in model fit, as evidenced by a lower AIC and a higher log likelihood for the full model.

The analysis to determine the significance of participants' prior knowledge as a random effect was conducted in a similar manner. The inclusion of people's prior statistics knowledge significantly improved the model fit ($\chi^2 = 16.49$, df = 1, $p < 0.00005$). This improvement was also reflected in better AIC (937.63 vs. 952.12) and BIC (961.57 vs. 972.64) scores, suggesting that understanding initial knowledge levels is crucial for accurately modeling learning outcomes.

Discussion

Impact of Gestures in Different Instructional Contexts

The improvements in test score observed in the "Algorithms with Gestures" and "Conceptual Instruction with Gestures" conditions, in comparison to other conditions, align with prior research (Church et al., 2004; Cook & Goldin-Meadow, 2006). It suggests that gestures not only complement verbal instructions but enrich the learning process by conveying implicit knowledge that is not captured through words alone. This study extends these findings by demonstrating that gestures are effective in adult education, particularly in enhancing comprehension and retention of statistical concepts, shown by the difference in increase from pretest to posttest in different conditions. In conditions where gestures were absent, the lesser omcrease illustrated the potential limitations of relying solely on verbal or textual information for teaching complex concepts like standard deviation.

The study shows that gestures enhance learning effectiveness because they can convey implicit knowledge that is not completely captured through verbal instruction alone. For instance, when an instructor uses hand movements across a histogram to illustrate the distances related to the mean, it visually emphasizes how the standard deviation might be affected—demonstrating whether it will be larger or smaller. Additionally, these hand gestures help illustrate concepts like the variability in data distributions, providing concrete imagery that assists learners in visualizing the differences between narrow and wide distributions. This direct guidance can reduce cognitive load by focusing learners' attention on specific areas of the histogram, which might otherwise require more effort to conceptualize independently. Through such non-verbal cues, gestures enrich the learning experience by adding depth and clarity to the instructional content, thereby fostering a more comprehensive understanding of the material.

Algorithmic & Conceptual

We observed no significant differences between the algorithmic and conceptual instructional conditions. As predicted, neither conceptual or algorithmic instruction was definitely beneficial to participants. This outcome suggests that neither instructional method uniformly benefits all participants which highlight the importance of considering individual differences and learning preferences. Some learners may favor a deeper understanding and application of underlying principles that enable them to solve mathematical problems conceptually. Conversely, some learners may perform better using surface-level, algorithmic problem-solving techniques for quick numerical answers. These variations highlight the importance of considering individual learner profiles, such as differences in math anxiety and prior statistical knowledge, as indicated by their pretest performance. This insight leads us to further explore how these individual differences affect learning outcomes within diverse educational approaches.

Math Anxiety and Prior Knowledge

In this study, math anxiety and prior knowledge were treated as random effects primarily to control their influence on the dependent variable—performance improvements in understanding standard deviation. Math anxiety, as reflected in our model, introduced a moderate level of variability in performance scores. It is important to note that these results primarily indicate variability in learning outcomes, rather than direct effects on the efficacy of the instructional methods. In the context of learning complex subjects like statistics, even a moderate level of anxiety can interfere with the cognitive processes necessary for understanding and applying statistical principles effectively. The variance associated with math anxiety was significant, although not the most dominant factor compared to pretest knowledge, suggesting that while it contribute to the variance of our model, the effectiveness of instructional strategies to alleviate math anxiety might broadly apply across conceptual and algorithmic teaching methods with or without gesture .

The substantial variance suggests that individuals with higher levels of prior knowledge likely found it easier to integrate new information and apply complex statistical concepts. Conversely, participants with lower pretest scores, representing limited prior knowledge, faced greater challenges during the learning process. Interestingly, the study's results indicated that despite the varying levels of prior knowledge, the instructional conditions did not differentially benefit participants based on their pretest classifications. This suggests that the instructional methods we designed were potentially robust enough to cater to a wide range of prior knowledge levels. On the other hand, it might indicate that the methods did not sufficiently address the specific needs of those with lower or higher prior knowledge bases.

Educational Implication

The effectiveness of incorporating gestures in both algorithmic and conceptual instructional methods underscores the potential of multimodal teaching strategies to enhance understanding and knowledge transfer in adult education. Our finding indicates that it is conducive to add gestures in mathematics lectures. By illustrating statistical principles dynamically, such as showing the impact of data variability on standard deviation through hand movements, this approach would enhance students' comprehension and improve their performance in assessments.

Furthermore, educators should be trained not only in the subject matter but also in effective delivery methods that include the use of gestures. Educational materials and curricula could be designed to explicitly include gesture-based explanations and activities, especially in online learning platforms since the need is more pronounced in recent days.

Despite no significant differences being observed between the algorithmic and conceptual conditions in terms of overall effectiveness, our finding is still instructive. It suggests that the choice between algorithmic and conceptual approaches should not be seen as mutually exclusive but rather as complementary. While gestures undeniably enhance learning, algorithmic instructions provide the procedures and formulas needed for quick calculations and problem-solving, while conceptual instructions foster a deeper understanding and the ability to apply knowledge in varied contexts. This variability indicates the importance of adaptive educational strategies that can accommodate diverse approaches to learning, rather than assuming a one-size-fits-all effectiveness for any particular method.

The findings from this research underline the efficacy of integrating gestures into both algorithmic and conceptual instructional approaches. It shows that such non-verbal cues significantly enrich the learning experience. Despite not observing significant differences between algorithmic and conceptual instructional methods in terms of overall effectiveness, the consistent improvements noted in gesture-integrated instruction suggest a potential benefit of gestures in educational settings. Future research could further explore the impact of gestures on learners' self-explanations for post-test problems, particularly in terms of clarity and accuracy.

Table 1.

	SD Score Increase					
Predictors	*Estimates*	*std. Error*	*CI*	*Statistic*	*p*	*df*
(Intercept)	-0.39	0.73	-1.83 – 1.05	-0.54	0.592	219.00
Participant Condition [Algo with Gesture]	0.84	0.36	0.13 – 1.55	2.34	**0.020**	219.00
Participant Condition [Concept no Gesture]	0.41	0.35	-0.27 – 1.10	1.20	0.232	219.00
Participant Condition [Concept with Gesture]	0.88	0.35	0.19 – 1.58	2.51	**0.013**	219.00
Random Effects						
σ^2	3.42					
$\tau_{00\ \mathrm{Math\_Anxiety}}$	0.20					
$\tau_{00\ \mathrm{Pretest\_binary}}$	0.73					
ICC	0.21					
$N_{\mathrm{Math\_Anxiety}}$	2					
$N_{\mathrm{Pretest\_binary}}$	2					
Observations	226					

Table 2. Participants' Performance

	Mean	SD
Pretest Accuracy	6.03	1.79
Post-test Accuracy	6.31	1.94
Performance Increase	0.28	1.97
Math Anxiety	3.22	1.41

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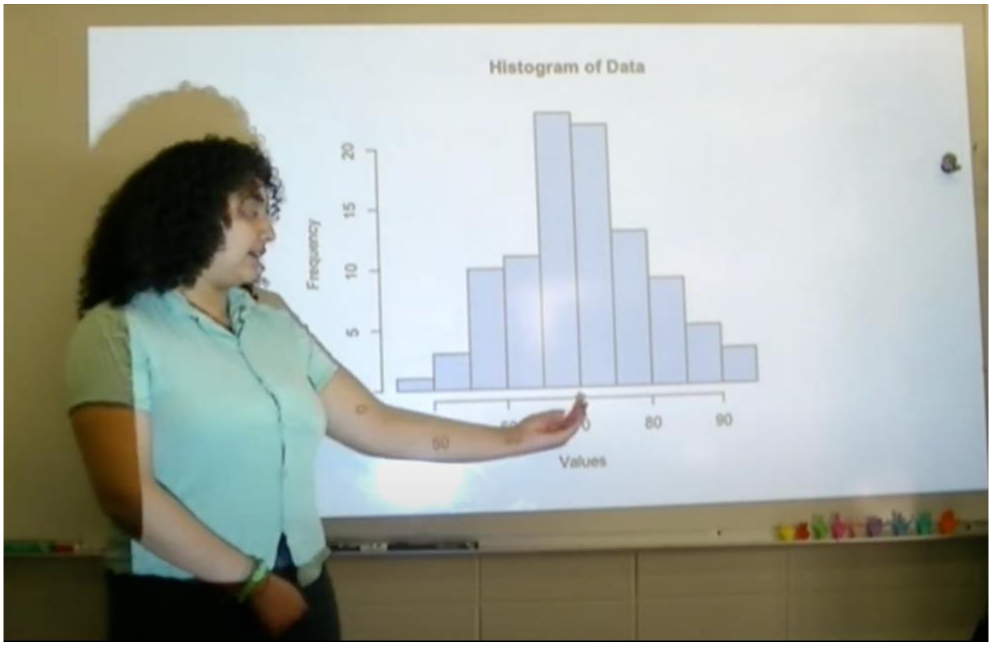
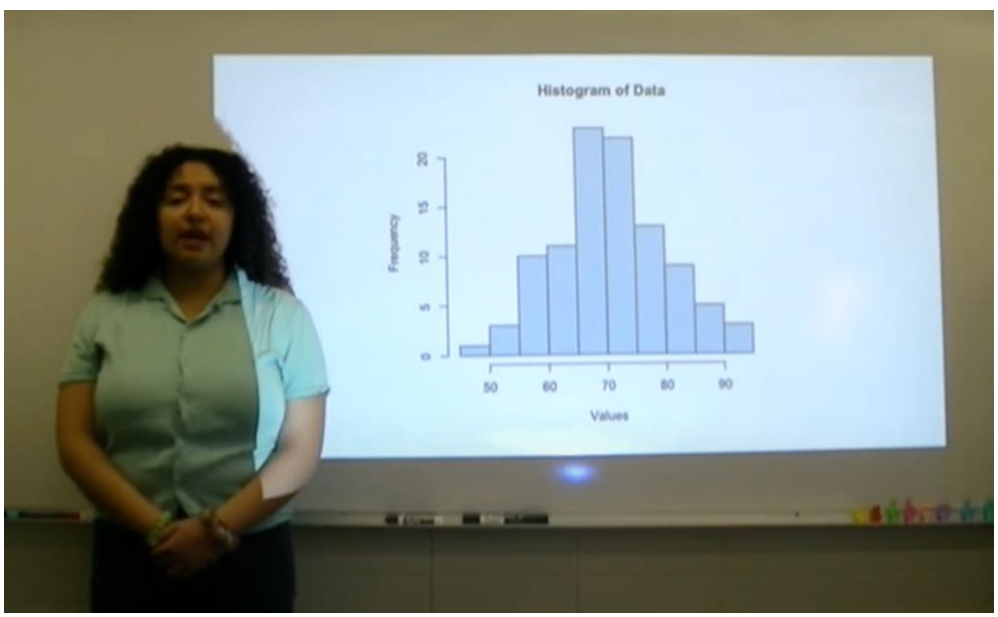
Appendix

Instruction with Gesture:



***Instruction:* "*Now, for every data point, we need to find how different it is from the mean or* how far it is from the mean."**

Instruction without Gesture:



Example of Verbal instruction:

Component	Algorithmic	Conceptual
Definition	The standard deviation is the average distance of data scores from the mean. The standard deviation tells us how variable, on average, the data scores are from the mean.	The standard deviation is the average distance of scores from the mean. It tells us how far, on average, the data scores are from the mean.
Determining the mean	Our first step is to find the mean of the data set. To calculate the mean, we just take all our scores, add them all up, and divide by the number of scores that we have. So now we've got our mean.	Our first step is to find the mean of the data set. The mean is a single number that gives us a sense of middleness, or the average. So now we've got our mean.
Finding the deviation score	Now, for every data point, we need to find how different it is from the mean or how much it deviates from the mean. To do this we subtract each data score from the mean.	Now, for every data point, we need to find how different it is from the mean or how far it is from the mean.

Problem with negative numbers deviation scores	And you might think that to find the standard deviation, we would just add up all of those deviation scores and divide by how many deviation scores we have, but that doesn't work. Why? Some of the scores are bigger than the mean, so if you subtract the mean from those scores, you're going to end up with a positive number. And some of the scores are smaller than the mean, so if you subtract the mean from those scores, you're going to end up with a negative number, and if you add them, all up they will always all add up to zero. And you can't divide zero by the number of deviation scores: you have to get the average or standard deviation. So we have to get rid of those negative numbers. How do we do that?	And you might think that to find the standard deviation, we would just add up all of those deviation scores and divide by how many deviation scores we have, but that doesn't work. Why? The mean is the balancing point, so whatever you've got on this side, you've got the same distance on the other side, so they're going to add up to zero. But you don’t need zero. You need to find out the average distance from the mean. How do we do that?