

THE INFLUENCE OF INFORMATION ADDED TO DATA

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We conducted a study to investigate the influence of a context on students' evaluation of data. Participants were given two data sets with the same mean but different standard deviations. Then they were asked which data set they thought was "better." Later, participants saw the same data sets again but now embedded in a context. Again, they had to choose the "better" method. Students' choices did not change significantly with additional information. However, when asked to justify their decision, the quality of the responses decreased when context was added. Further, 2/3 of the participants who based their decision on data justified their choice by referring to the standard deviation even though only 1/3 had sound knowledge about standard deviation.

INTRODUCTION

An important goal of science education is to enable students to reason rationally with data in different contexts (e.g., Next Generation Science Standards in the United States—National Research Council, 2013; KMK Bildungsstandards in Germany, 2004). However, students have difficulties in dealing with data and especially with conflicting evidence (e.g., Kanari & Millar, 2004; Kok et al., 2019; Lubben & Millar, 1996; Masnick et al., 2017). For this reason, it is important to learn more about how students make decisions and draw conclusions from contextualized data. Therefore, we conducted a study with 125 students to investigate the influence of a physical everyday context on students' evaluation of data.

THEORY

A wide range of research has investigated students' difficulties with scientific data (e.g., Chinn & Brewer, 1998; Kanari & Millar, 2004; Kok et al., 2019; Lubben & Millar, 1996; Masnick et al., 2017; Petrosino et al., 2003; Schulz et al., 2018). Masnick and Morris (2008) and Schulz et al. (2018) showed that students with limited statistical knowledge can select appropriate data sets and reason with properties of the data when they are given no additional information. Furthermore, students used intuition about the variance of data sets, e.g., they preferred data sets with lower standard deviations (SD) (Schulz et al., 2018).

However, it becomes more difficult when students are asked to evaluate experimental data embedded in a real-world context. Kanari and Millar (2004) investigated students' difficulties when facing conflicting data. They observed that students who saw conflicting evidence preferred to repeat measurements and choose "preferred" data to confirm their claim. Thus, the students seem to be led by their prior beliefs (see literature on confirmation bias, e.g., MacCoun & Perlmutter, 2015). Additionally, Masnick et al. (2017) observed that students' reasoning about data changes based on whether experimental data support their prior beliefs. Students reason based on data if the data support their claims. In contrast, when the data contradict their claims, students' justifications contained more context-based arguments. Thus, there is evidence that the context is responsible for this change in argumentation.

As far we know, no direct comparison has yet been made between how students evaluate data in a "context-free" and a "context-based" data comparison task. Therefore, we conducted an empirical study with the aim of discovering how context influences students' evaluation of data.

RESEARCH QUESTIONS

1. When given a choice between two different methods that generate one data set each (the two data sets have a different variance but the same mean), which data set do participants choose as the better one? 2. How is the decision influenced by putting the data sets in a context or not?

METHOD

The reported results in this paper are part of a larger study (pre-registered on AsPredicted 05/2020). The study was administrated digitally from September to December 2020, and a questionnaire was answered voluntarily, anonymously, and completely by 125 students attending the lectures “Introduction to Psychology” or “Introduction to Physics for Elementary School Teachers” in the United States and Germany. The mean age of all participants was 21.5 years (United States: $n = 101$, 19.2 years; Germany: $n = 24$, 31.1 years).

First, participants were given two data sets with the same mean but different SD. Then they were asked which data set—each representing results of an unknown measurement method—they thought was “better” for drawing conclusions. Additionally, they were asked to provide a justification for their decision. Later, participants saw the same data sets again but now embedded in a context, in which two different methods to measure the velocity of a bike were described (e.g., speedometer and GPS). Again, they had to choose the “better” method, and they had to justify their decision.

RESULTS

First, we analyzed students’ decisions of the “better” measurement method. When given a choice between two different methods, based on a data set without a given context, about half of the students (53%) chose the method with the lower SD (see Figure 1). If context was added to the data, the proportion of correct choice increases to 61%. Figure 1 shows that the proportion of incorrect decisions for a measurement method—the method with the higher SD—approximately doubles when context is added (from 12% to 22%).

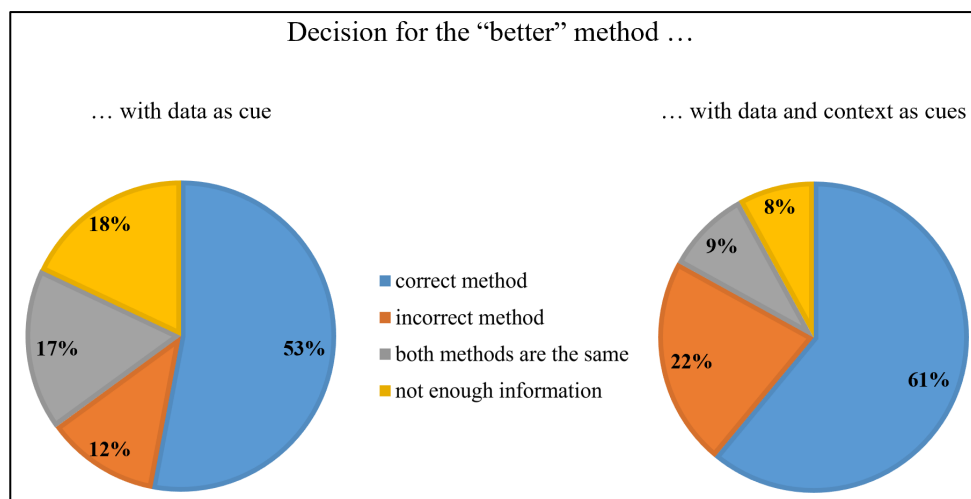


Figure 1. Distribution of students’ choices for the “better” measurement method with data as cue (on the left side) in comparison with data and context as cues (on the right side). The “correct” method was operationalized as the data set with the smaller SD.

A Wilcoxon signed-rank test showed no significant differences in the distributions between choosing a measurement method with data only ($M = 2$, scale from 0 to 2) and with data and context ($M = 2$) as cues ($T = 622$, $p = .53$, $r = -.04$). Thus, it appears that the decisions for the “better” measurement method were not influenced by the context.

Further, we analyzed students’ written justifications for their decisions, to examine whether context had an influence on participants’ decisions. Therefore, we developed a multilevel coding-manual to classify students’ written justifications, following the work of Kok (2022). First, the justifications were classified whether they were based on “data,” “context,” “data and context,” or “gut feeling.” Table 1 shows some typical examples of justifications. Next, all data-based justifications were analyzed with respect to which statistical variable was mentioned and what kind of comparison criterion was used. The statistical variables that were used in the students’ justifications were the “measured values,” “variance,” “mean,” and “standard deviation.” The

comparison criteria were the “mathematical calculability,” “order,” “accuracy,” “differences,” “largeness,” and “closeness” of different statistical variables. In addition, the context-based justifications were classified as “lack of knowledge,” “advantage of a measuring method,” and “subjective experience with a measurement method.”

Table 1. Categories of students’ justifications for their choice of a measuring method (first step; applicable for both situations, with and without context)

<i>Justification categories</i>	<i>Explanation</i>	<i>Prototypical examples</i>
Data-based	Only a statistical variable and criterion for comparison are mentioned.	“the standard deviation is smaller”
Context-based	The justifications are not based on data but on context.	“Measuring the velocity with a speedometer would give an accurate result, because error of measurement is eliminated to a good degree.”
Data and context-based	The justifications are based on both, data, and context.	“1. speedometer is a better tool to measure velocity, 2. SD is very small”
Gut feeling-based	The justifications indicate a kind of feeling as a decision base.	“it feels more right”

In Figure 2 it can be seen that about 75% of all students justified their decision for the “better” measuring method solely by referring to the data. This proportion decreases to around 50% of students when context is added. The proportion of students who justified their decisions by referring to the context increases from 10% to 29% of all students when adding the context.

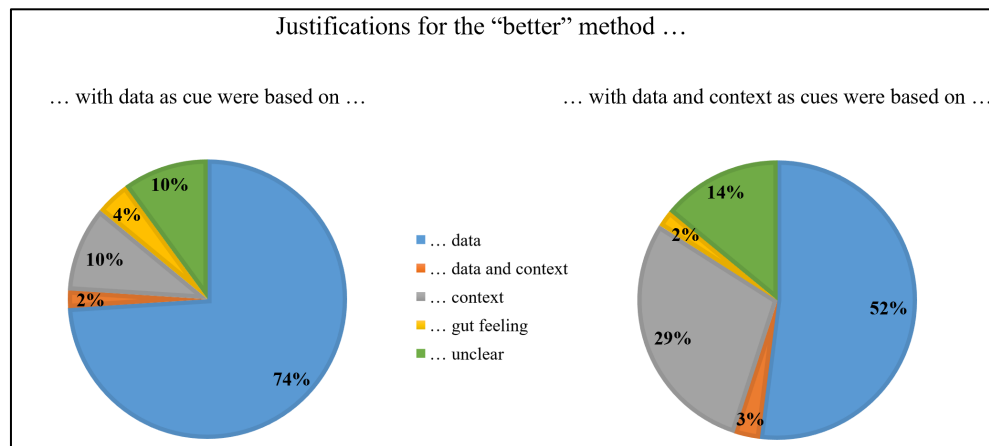


Figure 2. Distribution of students’ justifications (first step of the analysis) for the “better” measurement method with data as cue (on the left side) and with data and context as cues (on the right side)

A Wilcoxon signed-rank test showed a significant decrease in justification quality between the justifications for the decisions in the non-context part ($M = 2$, scale from 0 to 2) and the contextualized part ($M = 2$) ($T = 315,5$, $p = .006$, $r = -.17$). Justification quality was estimated—according to step 1 in the analysis—by whether the justification was based on data or data and context (high justification quality), context only (medium justification quality) or gut feeling (low justification quality). A more fine-grained assessment of the quality was done by further steps of the analysis (but are not reported here). About 67% of students (74% without context and 62% with context) who justified their decision for a measurement method by referring to the data mentioned the SD as the statistical variable. A majority of these students used “largeness” as a criterion (77% without context and 84% with context). However, only around 33% of them have sound knowledge about what an SD is (both, in the contextless and context case).

CONCLUSION

First, it appears that additional information about the context of a measurement may not distract students when evaluating empirical information because there were no significant differences between students' "context-free" and "contextualised" choices of the "better" measuring method. At a first glance, this contradicts other research (e.g., Kanari & Millar, 2004; Masnick et al., 2017). Even though participants were familiar with the concept of velocity, they may not know much about how velocities are actually measured. Thus, the context was of little distraction. However, when analysing students' written justifications for their decisions more closely, a significant decrease in quality of the explanations occurred. Even though the effect is weak, the justifications became more based on context and of lower quality, due to a lack of prior knowledge. This indicates that adding a little information may distract students from the data when they are asked to explain their decision in written text. From a didactical point of view, this is not a disadvantage because students try to integrate new information to solve a problem. However, if the essence of the information cannot be unpacked, students may refer to beliefs associated with the information instead of the information itself. This may hinder students' ability to reach correct conclusions. Thus, we assume that adding information only helps when students have enough background knowledge to draw valid conclusions from the information.

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