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Does a Name Make a Difference? Teaching Random Selection in the Classroom

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Does a Name Make a Difference? Teaching Random Selection in the Classroom

Abstract

In Statistics education, it is crucial to emphasize the foundational significance of random selection, which underpins statistical methodologies and ensures unbiased representation of populations in samples. However, students often struggle to grasp the concept's complexities, leading to challenges in applying random selection methods effectively. This paper examines the gap between students' theoretical understanding of randomness and their practical application of this concept. Using an Explanatory Sequential Design, this study presents an instructional activity aimed at teaching the concept of randomness in the selection process and proposes modifications to enhance student comprehension. The activity, implemented in undergraduate Statistics and Psychology courses, involved a name selection exercise designed to highlight the inherent biases in human decision-making. Despite students' initial recognition of the lack of randomness, evidence provided through the seemingly innocuous task of selecting names underscores how easily humans struggle with true random selection, indicating a need for deeper understanding. This activity can be used outside stats classrooms by instructors wishing to incorporate statistical reasoning in their lessons. Through qualitative analysis, it was revealed that students overlooked the introduction of statistical bias through specific selection criteria. This finding underscores the difficulties students face in achieving true randomness when applying the concept in practice. The paper encourages the use of a multi-method approach that integrates qualitative insights and quantitative analysis to enhance student comprehension. By adopting this approach, educators can better equip students to recognize and mitigate biases, thereby improving the efficacy of statistical reasoning instruction.

Keywords

statistics education, random selection, statistical reasoning, instructional activity, name selection exercise, statistical bias.

Cover Page Footnote

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Introduction

Random selection is foundational to statistical accuracy, supporting unbiased sampling and reliable inferences about populations. For students, understanding this concept prevents biases that can distort analyses and reinforces critical thinking essential for interpreting data accurately. Within statistics, achieving true randomness involves methods like simple random sampling, where each population member has an equal chance of selection, ensuring representative samples that support sound conclusions.

Despite its theoretical importance, students often face challenges applying random selection practically. While they may grasp the principle in the abstract, translating it into practice highlights common misconceptions and biases in human decision-making. This gap between theory and practice calls for instructional strategies that go beyond conceptual understanding, equipping students to recognize and mitigate unintentional biases in real-world scenarios.

Mastering random selection equips students for success beyond statistics, as fields like psychology, sociology, and public health rely on representative sampling for generalizable findings. The activity in this paper, a name selection exercise, guides students in identifying biases in random selection, deepening their comprehension and preparing them for advanced study. Through hands-on practice, students not only enhance their statistical reasoning but also develop critical data skills applicable in diverse disciplines and everyday decision-making.

Literature Review

Despite understanding the theoretical importance of random selection, applying it in practice presents significant challenges. As emphasized in the literature, there is a critical gap between recognizing the necessity of randomness and successfully implementing it in real-world contexts. For example, Steen (1990) highlights how innumeracy can contribute to inequality and hinder productivity while also drawing attention to the broader societal implications of failing to understand and apply mathematical concepts like randomness (see also Budhathoki et al. 2024). Furthermore, Karaali et al. (2016) stress the importance of clear definitions and effective communication in the field of quantitative literacy, indicating that even small misunderstandings or misapplications of concepts like random selection can lead to significant issues. Additionally, Grawe (2013) found that completion of various quantitative courses does not necessarily translate to improved quantitative reasoning-in-writing (QRW) skills and suggested that courses explicitly designed to teach QR thinking (i.e., first-year seminars), are more effective in fostering such skills. This highlights the challenge in translating theoretical knowledge to applied proficiency, a gap also seen in students’ understanding of randomness in this study.

Wagenaar (1972) conducted an extensive literature review focusing on human subjects' generation of random sequences, encapsulating numerous challenges later observed in subsequent studies and also discussed in this paper. The review delves into the subjective interpretation of randomness within psychology, detailing experiments where subjects were tasked with creating random series, factors influencing randomization experiments, metrics used to measure non-randomness by researchers, and the varying results obtained by different experimenters. The inherent difficulty in crafting a genuinely random sequence stems from human tendencies to introduce patterns and dependencies even when consciously attempting to generate random responses (Wagenaar 1972). Despite instructions to create random series, individuals often display systematic deviations from randomness, such as favoring specific response patterns, avoiding certain sequences, or exhibiting recurring trends. This phenomenon underscores the presence of inherent biases and tendencies among individuals during attempts to generate random sequences, resulting in outcomes that deviate from true randomness. Researchers encounter significant challenges in completely eradicating these patterns, underscoring the intricate nature of achieving pure randomness in sequences generated by humans (Treisman and Faulkner 1987).

The literature on human behavior and cognition, in relation to randomness and random selection tasks, reveals a nuanced understanding of systematic biases. Studies highlight how human-generated sequences often deviate from true randomness, indicating underlying cognitive processes and biases (see Schulz et al. 2012; Williams and Griffiths 2013; Towse et al. 2014). For example, Towse et al. (2014) observed preferential digit choices, while Schulz et al. (2012) demonstrated non-random patterns in human-generated sequences. This aligns with Brugger's (1997) proposition that such deviations result from cognitive interference rather than memory limitations.

The additional challenges humans face in generating truly random sequences are explored in Treisman and Faulkner (1987) and Figurska et al. (2008). They explore how factors such as memory, inhibition, and decision-making processes can influence randomness perception. These studies underscore debates about cognitive versus structural explanations for randomness generation, with Treisman and Faulkner (1987) proposing that internal random sources play a crucial role in response selection. Taken together, this body of literature unveils the intricate interplay among cognitive biases, decision-making processes, and structural theories while shedding light on the challenges that impede humans' capacity for random generation.

One such challenge faced in statistical research is the inherent human tendency towards specific values within a sequence, often influenced by the position of a value in that sequence. Treisman and Faulkner's (1987) research illuminated this phenomenon, revealing subjects' difficulties in producing truly random sequences due to biases towards or a preference for natural orderings. Additionally, Wood et al. (2011) explored how ballot position significantly impacted the number of votes received by candidates in London elections, highlighting the real-world implications of positional biases in decision-making processes.

Another notable challenge arises when dealing with random selection, particularly concerning the tendency to favor certain options over others. For instance, in the same study that explored how ballot position impacted the number of votes received by candidates, Wood et al. (2011) also identified name bias in electoral contexts. Moreover, numerous studies (Betrand and Mullainathan 2004; Cotton et al. 2008; Watson et al. 2011) focusing on hiring practices shed light on the prevalent role of name bias as a selection criterion, with applicants bearing anglicized or white names exhibiting higher chances of being hired. These findings collectively highlight the complexities and biases inherent in decision-making processes, urging a critical examination of factors influencing choices and outcomes.

Given these considerations, the authors sought to introduce one such exercise in their classes to elucidate the concept of *random* in the process of random selection. This paper addresses the gap between understanding the concept of random selection in theory and applying it in practice, as noted by Steen (1990) and Karaali et al. (2016). It outlines the instructional design, procedure, and results of teaching random selection.

Methods

The objectives of this instructional activity are twofold: firstly, for students to identify instances where selections made by individuals, including themselves, lack randomness, and secondly, for them to adjust their selection method to ensure randomness (e.g., assigning numbers to names and utilizing a random number generator for selection).

Participants in this study were students from a community college in the northeast United States. To maintain confidentiality and anonymity, demographic information was not collected for participants. According to data provided in the institution's 2022–2023 factbook, students represent 106 countries with 69 different languages spoken. Institution wide, 30% of students identify as Asian or Pacific Islander, 28% Black, 27% Hispanic, and 15% White. The average student age is $M = 23.1$ years, with 52% identifying as female and 48% identifying as male. For registered students 63% were full-time and 37% part-time.

The name selection activity was administered across five sections of undergraduate Statistics courses, one section of Social Psychology, and one section Research Methods ($n = 92$) from Summer 2021 to Fall 2023. The statistics course includes a total of four hours of instruction per week, with one hour designated for lab work in a computer room. One section of the statistic course followed a hybrid format with two hours synchronously online and two hours in-person. The psychology courses were three-hour courses that met once a week and emphasized techniques for conducting sound research. Both psychology sections were conducted in-person. The study was IRB approved (#2012-0393).

Instructional Design

Although much of the literature discusses the results of studies using a number selection activity to teach random selection, this study utilized a name selection activity to present to the students. The aim was for students to recognize the absence of randomness more readily in their outcomes due to their own biases, which we were inclined to believe might be easier to perceive with names compared to number selections. In previous semesters while teaching random selection, in Statistics and Psychology classes, number exercises had been used. However, when students were shown the results, they did not seem to appreciate the importance of one number having a higher frequency over another. Asking the students to select from a list of names, rather than a list of numbers, helped highlight the relevance of the results.

The study followed an Explanatory Sequential Design, in which both quantitative and qualitative data were collected concurrently, with the qualitative data used to further explain and contextualize the initial quantitative findings. The pool of common names was derived from a Google search for “most popular boy names” and “most popular girl names,” and a random subset of eight common female-associated and male-associated names was generated using Microsoft Excel. A separate pool of uncommon names was generated by the authors based on names from class rosters from previous semesters (minimum of one year prior). These rosters spanned a variety of subject matter, and names were classified as uncommon based on the researchers’ judgment. A random subset of 12 female-associated and male-associated names was also selected from this pool using Excel.

The activity unfolded in three phases. Initially, students received two lists containing 20 male-associated names and 20 female-associated names. They were tasked with selecting a random sample of exactly five (5) names from each list. The lists were presented to students digitally via a Google Form survey, with all students seeing the same computer-randomized list of names in the same order, as the randomization remained unchanged for all subsequent dissemination. Students made their selections using the “check box” feature in the Google Form survey. In the second phase, participants were presented with data visualizations of the pooled results from students who also completed the activity in previous semesters, depicted in bar chart format for each set of names. Drawing from prior research, the authors anticipated a non-uniform distribution in both name selection bar charts. Subsequently, a class discussion, guided by the instructor, encouraged students to collectively analyze the implications of the displayed bar charts. This guided discussion was designed to lead students toward recognizing the inherent bias in their initial selection processes. Instructors used specific prompts such as, “What patterns do you notice in the distribution of names?” and “Why might some names have been selected more frequently than others?” to foster critical thinking. Instructors actively emphasized to students the improbability of achieving truly random name selections, as indicated by a non-uniform distribution.

In the third and final phase, students were instructed to perform another round of random name selection from the same lists provided initially. Again, participants experienced the names in the same order without individualized randomization in the presentation. Additionally, alongside their selections in phases 1 and 3, students were asked to provide free-response explanations of their selection process. These qualitative data were systematically coded by the researchers into categorical themes for subsequent analysis. The time elapsed between phases was approximately two weeks, although this varied slightly depending on course schedules and accommodating for students catching up on initially completing phase I of the activity.

To provide context for the names used in this activity, we reference a comprehensive dataset that documents the relative frequency of first names across six mutually exclusive racial and ethnic groups, based on US mortgage application data (Tzioumis 2018). This dataset, derived from self-reported information, includes 4,250 first names and offers insights into how names are distributed across categories such as “Hispanic or Latino,” “Non-Hispanic White,” “Non-Hispanic Black or African American,” and others. By utilizing this dataset, we can better understand the demographic associations of the names selected by students, which plays a critical role in highlighting the potential biases influencing their name choices. Tables 1a and 1b in this study present the relative frequency of the names used in the selection activity, demonstrating the representativeness of the names within broader racial and ethnic contexts. This background is essential for understanding how student biases may mirror societal patterns in name recognition and preference.

Table 1a
Relative Frequency of Female-Associated Names Selected in the Name Selection Activity by Racial and Ethnic Group (Based on US Mortgage Application Data, Tzioumis 2018)

First Name	Number of occurrences in the combined mortgage datasets	Percent Hispanic or Latino	Percent Non-Hispanic White	Percent Non-Hispanic Black or African American	Percent Non-Hispanic Asian or Native Hawaiian or Other Pacific Islander	Percent Non-Hispanic American Indian or Alaska Native	Percent Non-Hispanic Two or More Races
Smaragda	0	0	0	0	0	0	0
Chamieda	0	0	0	0	0	0	0
Isamar	0	0	0	0	0	0	0
Monique	458	8.297	62.882	24.017	3.712	0	1.092
Meagan	0	0	0	0	0	0	0
Mirian	0	0	0	0	0	0	0
Yanzhen	0	0	0	0	0	0	0
Supriya	0	0	0	0	0	0	0
Nusaibah	0	0	0	0	0	0	0
Jennifer	19356	1.943	94.436	1.199	2.216	0.072	0.134
Shanaiya	0	0	0	0	0	0	0
Kelly	7218	0.707	96.814	0.707	1.538	0.139	0.097
Katherine	4802	1.833	94.252	1.562	2.187	0.083	0.083
Arisa	0	0	0	0	0	0	0
Manjinder	0	0	0	0	0	0	0
Angelisse	0	0	0	0	0	0	0
Nyanda	0	0	0	0	0	0	0
Rebecca	7229	3.486	94.052	0.83	1.369	0.124	0.138
Emily	2809	1.673	92.026	1.709	4.201	0.142	0.249
Heather	5801	0.896	97.397	0.896	0.517	0.138	0.155

Table 1b
Relative Frequency of Male-Associated Names Selected in the Name Selection Activity by Racial and Ethnic Group (Based on US Mortgage Application Data, Tzioumis 2018)

First Name	Number of occurrences in the combined mortgage datasets	Percent Hispanic or Latino	Percent Non-Hispanic White	Percent Non-Hispanic Black or African American	Percent Non-Hispanic Asian or Native Hawaiian or Other Pacific Islander	Percent Non-Hispanic American Indian or Alaska Native	Percent Non-Hispanic Two or More Races
Walter	3147	4.512	85.796	7.69	1.875	0.032	0.095
Sam	727	3.026	73.04	4.539	19.257	0.138	0
Feyaz	0	0	0	0	0	0	0
Abhishek	18	0	0	0	100	0	0
Ganeshwar	0	0	0	0	0	0	0
Anthony	10335	5.099	84.161	7.199	3.154	0.174	0.213
Shihab	0	0	0	0	0	0	0
Huberney	0	0	0	0	0	0	0
David	48307	3.223	92.808	1.393	2.393	0.106	0.077
Jaesuk	0	0	0	0	0	0	0
Xiaochong	0	0	0	0	0	0	0
Parmvir	0	0	0	0	0	0	0
Freddy	123	62.602	26.829	6.504	4.065	0	0
Victor	2896	40.711	47.479	4.869	6.768	0.069	0.104
Asadallah	0	0	0	0	0	0	0
Kymani	0	0	0	0	0	0	0
Tanvir	0	0	0	0	0	0	0
Diego	198	83.333	15.152	0	1.01	0	0.505
Chris	2500	2.2	91.68	1.6	4.28	0.12	0.12
Jaedon	0	0	0	0	0	0	0

Procedure

The activities were part of class assignment and students were allowed to self-select to participate with the option to remain anonymous. Students were not offered incentives to complete the activities and for those choosing not to participate, there were no negative consequences.

Phase 1. Participants were instructed on the need for random sampling and methods of random sampling with a reminder that human beings do not typically produce random samples. Participants were also instructed on how to use software for random sampling (i.e., Excel). Students were then asked to complete the name selection activity (pre-test).

Phase 2. Following the completion of the first activity, participants were shown the results of students who completed the activity in previous semesters and were asked to discuss and comment on the results of their peers from previous semesters. The results were in the form of bar graphs generated by Google forms. These results clearly demonstrated bias in sampling. A guided discussion followed, with instructors using targeted prompts to encourage reflection on the implications of observed biases. Students were prompted to critically assess the impact of biases on random selection, aiding in their understanding of the barriers to true randomness in human behavior. The discussion in the classroom was designed to increase students' awareness of the presence and importance of bias, in the results they were shown, with the hope of reduced selection bias in the next name selection phase.

Phase 3. Finally, students were asked to complete the name selection activity a second time (post-test) while having access to the results of previous semesters. For both pre and post, students were asked to complete the activities outside of class time and the instructions were the same for pre and post.

Results

As anticipated, the outcomes following the initial selection phase revealed that the students' name selections deviated from randomness. The Chi-square goodness-of-fit test indicated that the distribution of selected names for both male and female associations (Figs. 1a and 1b, respectively) did not align with a uniform distribution (χ^2_{Male} = 156.56; df = 19; $p < 0.001$: χ^2_{Female} = 106.80; df = 19; $p < 0.001$). Similar results were obtained in phase 3 after students were informed of the phase 1 findings and their implications (χ^2_{Male} = 135.99; df = 19; $p < 0.001$: χ^2_{Female} = 111.20; df = 19; $p < 0.001$).

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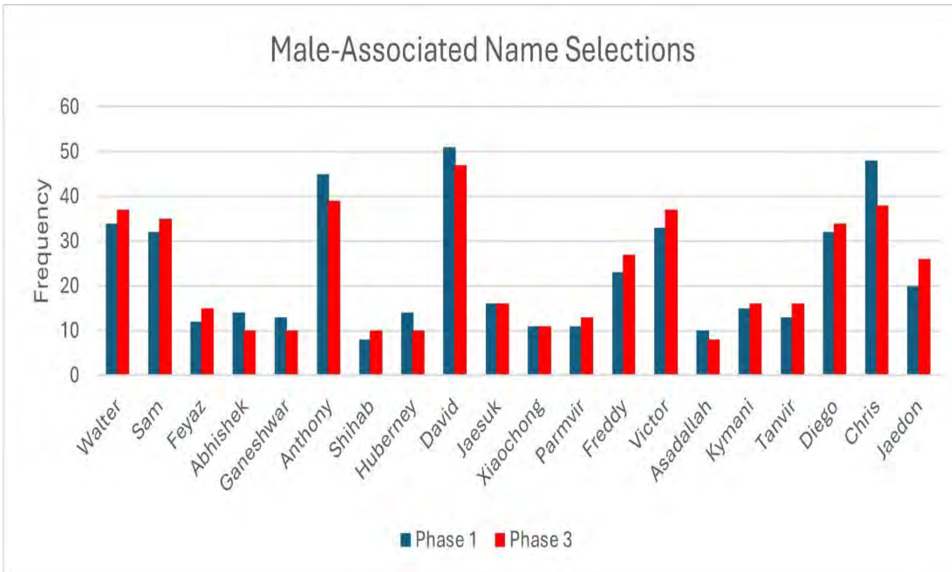

Figure 1a. Distribution of selected male-associated names

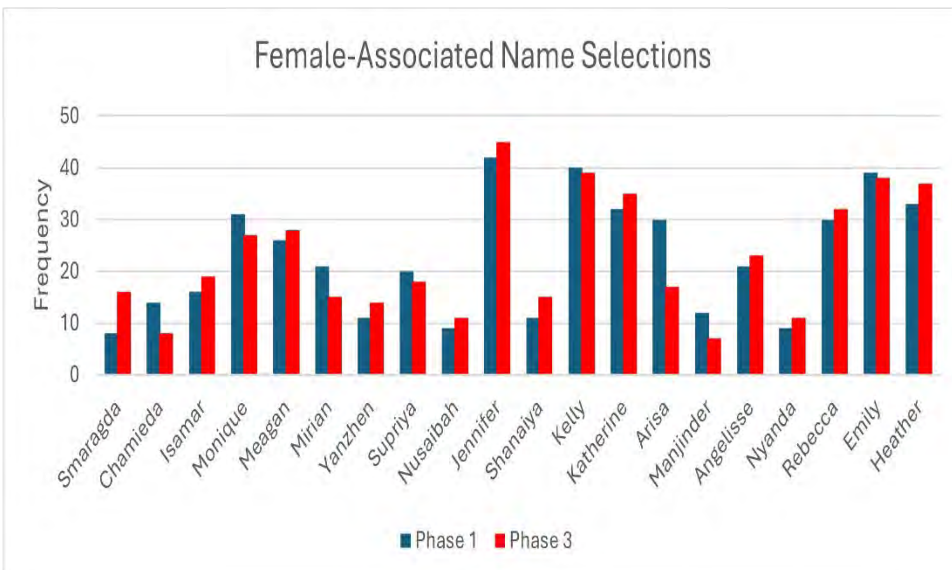

Figure 1b. Distribution of selected female-associated names

The correlation coefficient and coefficient of determination were calculated to evaluate the potential impact of the presentation order of names on students' selections (Figs. 2a, 2b, 2c, and 2d). In phase 1, a weak positive correlation (r = 0.37) was observed between the presentation order of names and the frequency of female-associated name selections, with approximately 14% of the variability in selection frequencies attributed to this linear relationship. However, for male-

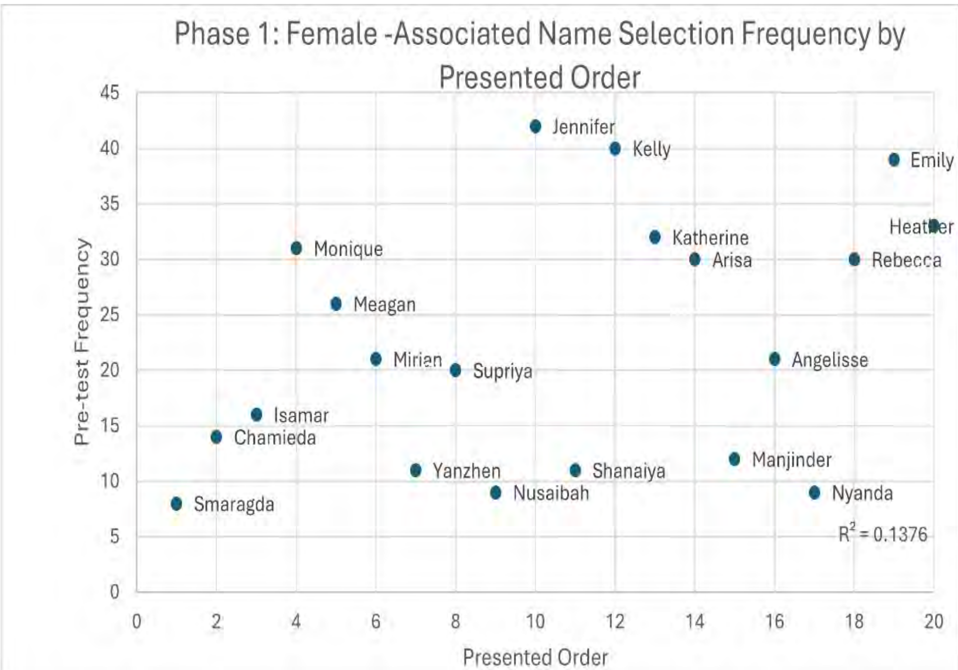

Figure 2a. Phase 1: Female-associated name selection frequency by presented order

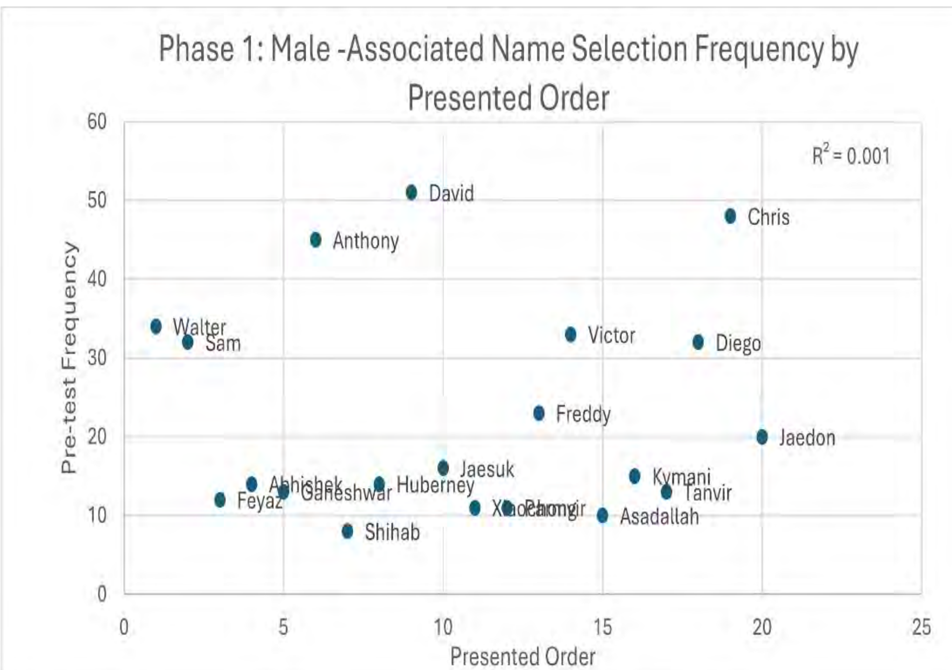

Figure 2b. Phase 1: Male-associated name selection frequency by presented order

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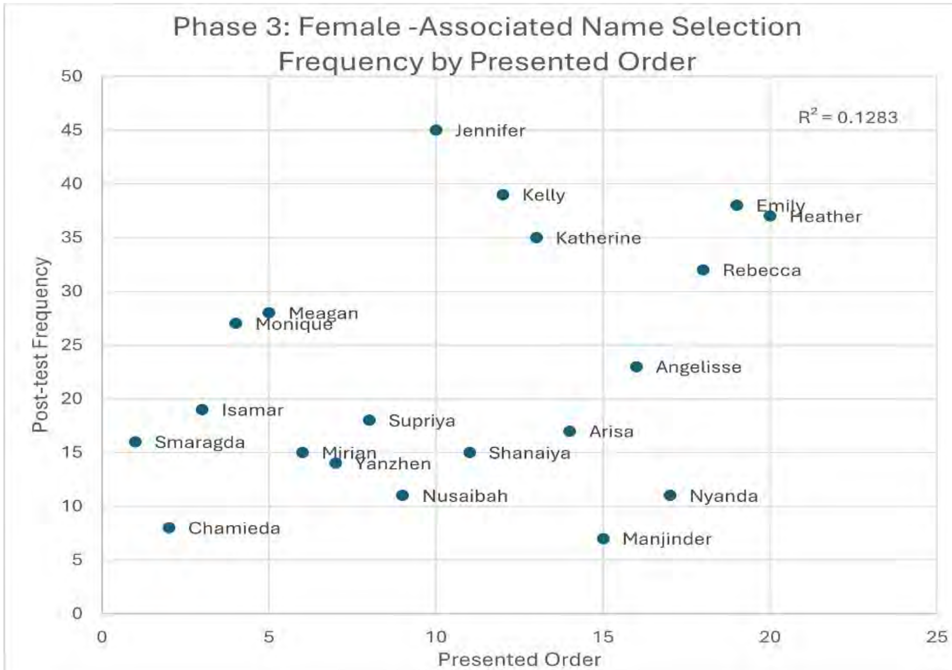

Figure 2c. Phase 3: Female-associated name selection frequency by presented order

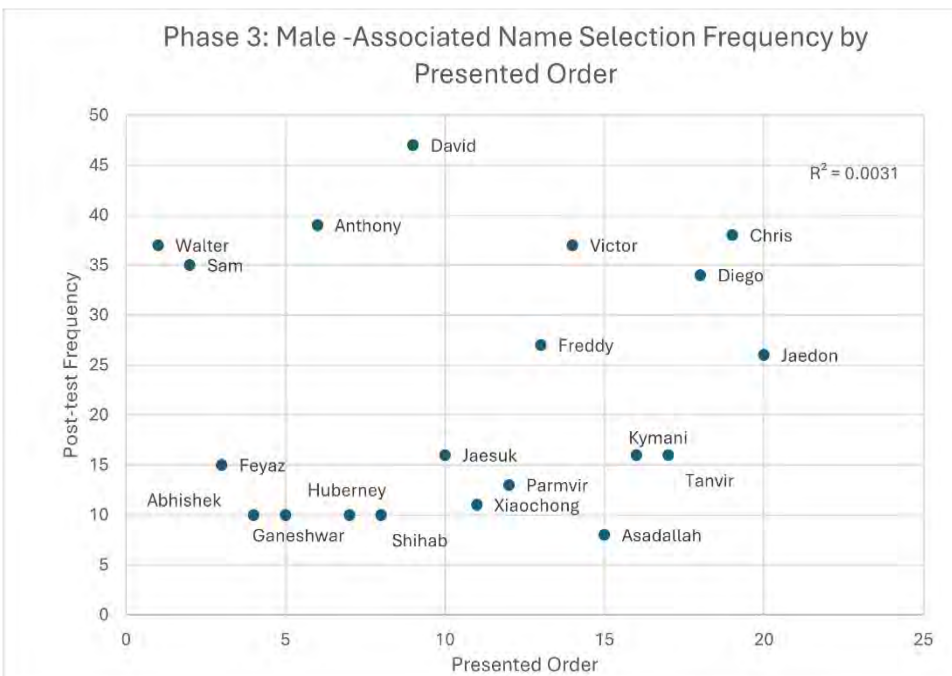

Figure 2d. Phase 3: Male-associated name selection frequency by presented order

associated name selections in the same phase, a negligible linear correlation (r = 0.03) was found, explaining only about 0.1% of the variability.

Moving to phase 3, a similar pattern emerged. The correlation coefficient for female-associated name selections was 0.36, indicating a weak positive correlation that explained around 13% of the variability in selection frequencies. Conversely, the correlation coefficient for male-associated name selections remained low (r = 0.05), explaining approximately 0.3% of the variability. These results collectively suggest that the order of name presentation had minimal systematic influence on name selections.

In addition to selecting names, students were tasked with providing explanations for their name choices in both phase 1 and phase 3 of the activity. Below is a summary of the codes and the coding methods employed by the raters for the explanations accompanying female-associated and male-associated name selections, along with the corresponding statistical results:

1) Familiarity to the Student: The student chose the name because it was familiar to them.
2) Uncommon or Unfamiliar to the Student: The student chose the name because it was unfamiliar to them or uncommon in their experience.
3) Random Selection Attempt: The student made an erroneous random selection attempt, for example engaging in systematic sampling.
4) Random Selection: The student used some type of random selection method, such as assigning every name a number and then having a random number generator choose five names.
5) Desirable Name: The student selected the name because they thought either the pronunciation or the spelling made the name appealing.
6) Miscellaneous: The student's name selection did not fit any of the above categories.

Phase One: Female-associated Name Selection

In the initial phase of our instructional activity, two raters coded explanations provided by students for their female-associated name selections. The agreement between these raters was 62.64%, indicating a moderate level of agreement. The Cohen's Kappa coefficient was calculated at 0.5331, highlighting a moderate agreement beyond what would be expected by chance alone. The low probability p-value (0) indicates that this level of agreement is unlikely due to random chance, lending credibility to the coding process and demonstrating statistical significance in the observed agreement.

Phase One: Male-associated Name Selection

Similarly, during the first phase, raters evaluated explanations for male-associated name selections. The agreement between them was slightly higher at 68.89%, with a corresponding Cohen's Kappa coefficient of 0.5939, also reflecting a moderate level of agreement beyond chance. The low p-value (0) suggests that this agreement is statistically significant and not merely coincidental.

Phase Three: Female-associated Name Selection

Moving to phase three, where students again provided explanations for both female and male-associated name selections, the agreement between raters for female-associated names increased to 71.43%. The Cohen's Kappa coefficient improved to 0.6458, indicating a substantial level of agreement beyond chance. The very low *p*-value (0) further reinforces the reliability of the coding process in this phase and signifies statistical significance in the observed agreement.

Phase Three: Male-associated Name Selection

In phase three, the agreement for male-associated name selections was 64.44%, slightly lower than for female-associated names but still showing a moderate level of concordance. The Cohen's Kappa coefficient for male selections was 0.5544, indicating moderate agreement beyond chance. The low *p*-value (0) once again underscores the statistical significance of the observed agreement.

The results of the interrater reliability analysis show that our coding method was consistent and reliable across different stages and categories of the name selection activity. The moderate to substantial agreement, indicated by Cohen's Kappa coefficients and low *p*-values, confirms that our coding effectively captured the distinctions in students' explanations for their name choices. These statistically significant findings highlight the strength of our analytical approach. However, prior to embarking on a categorical analysis of the students' name selections within each phase, a crucial prerequisite entails the attainment of consensus among raters regarding the code descriptors corresponding to each student's selection rationale. Hence, a collaborative effort ensued amongst the raters, wherein a comprehensive discussion was undertaken to harmonize their coding approaches, culminating in a unanimous consensus regarding the code allocations for each student's selection rationale.

The subsequent analysis was conducted following the raters achieving consensus on coding. Despite a consistent sample size (n = 92) across both phases 1 and 3, there was one fewer response to the query seeking an explanation of name selections for both females and males in phase 3 compared to phase 1. Additionally, two participants explained their female-associated name selections in phase 3 but did not offer an explanation for their male-associated name selections. Consequently, relative frequencies are deemed more suitable for facilitating comparisons across groups (refer to Figs. 3a and 3b). Notably, relative frequencies exhibited similar trends for each category in both phases, with "Familiarity to the Student" persisting as the primary criterion for selection. This consistency suggests no significant alterations in selection criteria over the course of this repeated measure.

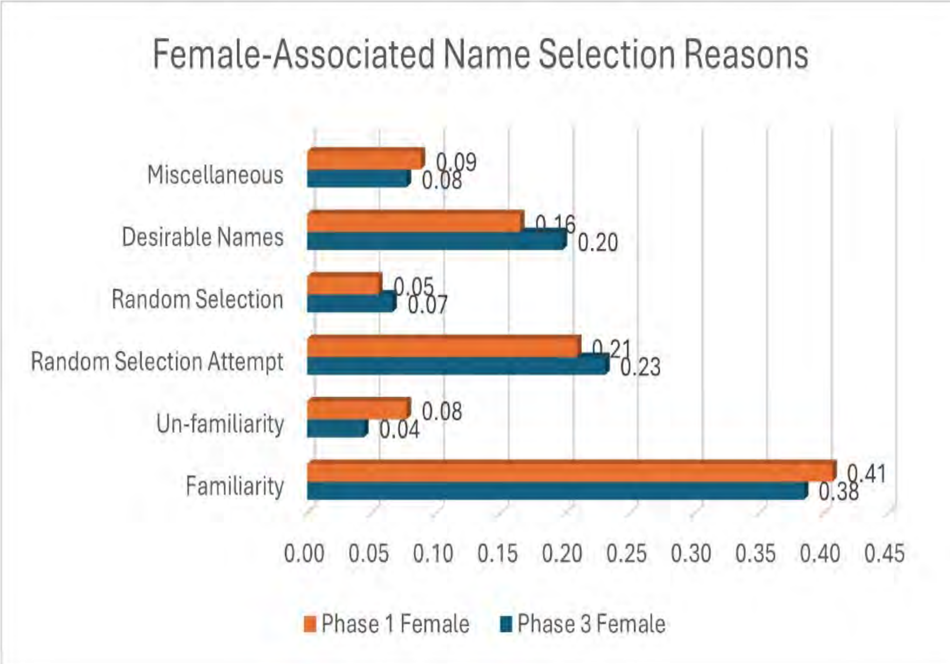

Figure 3a. Name selection reasons for female-associated names

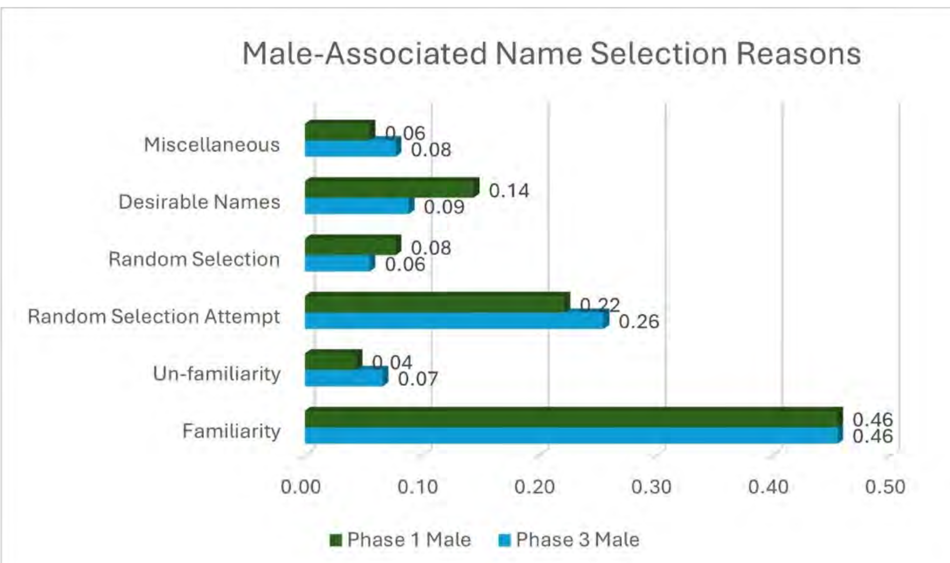

Figure 3b. Name selection reasons for male-associated names

The outcomes derived from the Bowker test conducted on participants' explanations for female and male-associated name selections further reveal a lack of compelling evidence to substantiate a significant shift in symmetry concerning

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participants' rationales for name selections between phase 1 and phase 3 *(Female-associated names: χ2(13, N = 91) = 8.81, p = .7872; Male-associated names: χ2(13, N = 89) = 14, p = .3738)*. Correspondingly, the contingency tables portraying the explanation of female-associated name selections (Table 2a) and male-associated name selections (Table 2b) illustrate that no more than 7 participants altered their rationale for name selection from phase 1 to phase 3. Moreover, the utilization of random selection in the name selection process marginally improved for female-associated names chosen (phase 1: 5.5%; phase 3: 6.5%) and slightly diminished for male-associated names selected (phase 1: 7.9%; phase 3: 5.6%), with random selection persisting as the least probable rationale for choosing either female or male-associated names in each phase.

Table 2a
Explanations of Female -Associated Name Selections

	Phase 3						
Phase 1	**Miscellaneous**	**Familiarity**	**Unfamiliarity**	**Random Selection Attempt**	**Random Selection**	**Desirable Names**	Total
Miscellaneous	1	2	0	1	0	4	8
Familiarity	2	23	1	7	0	4	37
Un-familiarity	2	1	2	0	1	1	7
Random Selection Attempt	0	5	1	10	2	1	19
Random Selection	0	1	0	1	3	0	5
Desirable Names	2	3	0	2	0	8	15
Total	7	35	4	21	6	18	91

Table 2b
Explanations of Male-Associated Name Selections

	Phase 3						
Phase 1	**Miscellaneous**	**Familiarity**	**Unfamiliarity**	**Random Selection Attempt**	**Random Selection**	**Desirable Names**	Total
Miscellaneous	0	3	0	1	0	1	5
Familiarity	1	29	3	6	0	2	41
Unfamiliarity	3	0	1	0	0	0	4
Random Selection Attempt	1	3	1	11	2	2	20
Random Selection	1	0	0	2	3	1	7
Desirable Names	1	6	1	2	0	2	12
Total	7	41	6	22	5	8	89

Discussion & Conclusion

The study highlights a significant gap between students' theoretical understanding of random selection and their ability to apply this concept in practice. While students initially demonstrated an awareness of the role random selection plays in statistical interpretation, their selection criteria remained largely unchanged from phase 1 to phase 3 of the instructional activity. This outcome initially surprised the authors, as students grasped the importance of randomness, but the results reveal that this understanding did not translate into practical application.

The observed deviations from expected random patterns, particularly the influence of familiarity bias in selection tasks, underscore the complexity of achieving true randomness. For example, the lack of a more uniform distribution in students' responses during phase 1 should have indicated that their choices, and the reasons for them, were not aligned with true random selection. The data suggests that while students understood the theoretical necessity of randomness, their selections were often skewed by underlying biases, such as the tendency to favor familiar names. This cognitive bias compromised the randomness of their choices, highlighting the challenges in human decision-making processes when theory is confronted with real-world scenarios (Jones 2019).

This gap between theory and practice is well-documented in the literature. Steen (1990) discussed the broader societal implications of innumeracy, noting how a superficial understanding of mathematical concepts like random selection often fails to translate into practical application. Similarly, Karaali et al. (2016) emphasized the need for precise definitions and effective communication in quantitative literacy, suggesting that a lack of clear understanding leads to the misapplication of fundamental concepts like randomness.

To address this issue, educators should emphasize data indicators that suggest deviations from random selection, using them as teaching moments to explore how personal experiences and cultural contexts can subtly influence data collection and analysis. Upon reflection, we infer that students in this study overlooked how adhering to specific selection criteria introduced statistical bias, rendering true random selection unattainable. This insight underscores a common issue in statistical education, where the focus on quantitative methods often neglects the value of qualitative insights, particularly in understanding and mitigating cognitive biases.

The absence of qualitative discussions within this instructional activity mirrors a broader trend in statistics courses, where the focus on quantitative methods often limits students' opportunities to explore biases that can shape data interpretation. While statistical analysis relies on significance testing to evaluate chance, qualitative methods can reveal how subjective factors influence outcomes (Fetterman 2009). However, a growing trend toward multi-method approaches—

combining qualitative and quantitative methods—offers a solution. These approaches allow for the statistical quantification of phenomena while providing a broader understanding of the subject matter. By integrating this multi-method approach, educators can help students better grasp how biases manifest in data collection and interpretation, and how they can be mitigated.

Ultimately, these findings suggest that instructional strategies should not only teach the conceptual importance of randomness but also address the practical challenges of implementing it. By fostering deeper engagement with the complexities of human decision-making, educators can better prepare students to apply statistical reasoning more effectively, both in academic contexts and the real world.

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