Empowering Girls in STEM: The Role of Female Representation in Shaping Children's Structural Reasoning About Gender Disparities

Liz Kim

Department of Psychology, University of Chicago

Author Note

Correspondence concerning this article should be addressed to Liz Kim, Department of Psychology, University of Chicago, 5848 S University Ave, Chicago, IL 60637, USA, Email: lizkim@uchicago.edu

Abstract

Gender bias in STEM educational materials remains a significant barrier to gender equity, with textbooks and online resources often underrepresenting female scientists. This study examines whether children recognize the lack of female scientists as a structural barrier in STEM by presenting them with two hypothetical competition scenarios: robot-building and puzzle-solving. In the robot-building scenario, 96 children aged 5–8 children were randomly assigned to one of three conditions varying the representation of male and female scientists in textbooks. Open- and closed-ended questions assess their reasoning about gender disparities, with the puzzle-solving competition serving as a baseline to test generalization. Findings suggest that structural explanations increased and intrinsic explanations decreased in the Within condition, though generalization across domains was inconclusive.

Keywords: Gender Bias in STEM, Structural Reasoning, Educational Materials

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Gender bias in STEM often hides in plain sight, subtly embedded in textbooks and classroom materials. Women are significantly underrepresented in school textbooks, particularly in professional STEM contexts (Crawfurd et al., 2024; Kerkhoven et al., 2016). An analysis of over 1,200 textbooks from 34 countries found that female figures appear less frequently in STEM contexts, reinforcing traditional gender roles and shaping students' perceptions of who is suited for science fields (Crawfurd et al., 2024). Similarly, online science education materials tend to portray male characters as more engaged in STEM activities, reinforcing the association of STEM with masculinity (Kerkhoven et al., 2016). When girls consistently see male scientists, mathematicians, and engineers conveyed as the primary figures of success, they receive an implicit message about who "belongs" in these fields, which can discourage them from envisioning themselves as future STEM professionals (Master, 2021). Thus, balanced gender representation in educational materials is important, as biased portrayals can dissuade girls from pursuing STEM by influencing their beliefs about their abilities and potential in these fields.

Psychological Mechanisms Underlying Gender Stereotypes in STEM

Master (2021) explains that stereotype threat occurs when individuals become aware of negative stereotypes about their social group. For example, when girls are reminded of the stereotype that "boys are better at math," they may experience heightened anxiety and reduced confidence, leading to lower performance. Over time, this repeated experience of underperformance can create a self-fulfilling prophecy, where girls disengage from STEM fields altogether to avoid the stress of confronting stereotypes. Social identity theory further explains how girls' sense of belonging and self-concept are influenced by group identification. This theory posits that individuals derive a significant part of their identity from the social groups to which they belong (Kim et al., 2018). For girls, strongly identifying with their gender may lead them to internalize the perception that STEM is a "male" domain, particularly when female scientists are absent in educational materials. This lack of female representation reinforces the belief that

STEM is not a space where they belong, further discouraging them from participating in STEM activities (Kim et al., 2018; Master, 2021). Therefore, female figures in STEM textbooks are crucial; they provide positive examples that challenge gender stereotypes, demonstrating that women can thrive in STEM.

The Role of Structural Reasoning in Reducing Gender Disparities

Female representation not only inspires girls to consider STEM careers but also helps them understand structural barriers to gender equity, an approach more effective than individual reasoning; individual reasoning often places the burden on girls to overcome obstacles alone, while structural reasoning encourages them to view and address challenges as part of broader societal structures. When girls view gender gaps in STEM as personal limitations, it reinforces stereotypes and lowers self-efficacy; in contrast, structural reasoning reframes these gaps as outcomes of systemic barriers—such as biased educational resources or gender discrimination—that restrict women's participation in STEM (Amemiya & Bian, 2024). Female figures are pivotal in creating an environment that prevents individual reasoning. The representation can normalize women's presence in STEM, signaling that success in these fields is not limited to men, reducing stereotype threat (Master, 2021). Also, it can help girls begin to consider systemic factors rather than solely personal shortcomings as explanations for gender disparities (Breda et al., 2023). Additionally, structural reasoning aligns with social identity theory by reinforcing that girls are not inherently excluded from STEM. Instead, they are part of a group facing societal bias, fostering a sense of belonging and empowering them to challenge structural inequities.

The Impact of Female Representation on STEM Engagement

Exposing girls to female representation in STEM can significantly enhance their motivation to pursue STEM careers and reduce gender biases. Kong et al. (2020) finds that diverse STEM female figures in media and educational settings foster a positive association of women with STEM fields from an early age. Moreover, encounters with female scientists can increase girls' STEM aspirations and counteract stereotypes (Breda et al., 2023; González-Pérez et al., 2020; Master, 2021).

Current Study

Despite increasing efforts to promote gender equity in STEM, girls continue to encounter significant barriers. While much of the literature focuses on how female representation influences participation and aspiration in STEM, one often overlooked factor is its impact on how children attribute gender disparities in STEM achievements—whether they view them as rooted in personal limitations or structural barriers. My research contributes to the literature by addressing this gap and investigating how exposure to different representations of scientists in educational materials influences children's reasoning about gender disparities. This study is significant because, by uncovering how such exposure shapes their interpretations, it can inform interventions designed to challenge stereotypes and empower girls to envision themselves as successful participants in STEM fields.

How does exposure to structural information, such as the gender of scientists in STEM textbooks, impact children's structural reasoning about gender-based disparities in STEM achievement? We hypothesize that exposure to structural information demonstrating that the gender of scientists in STEM textbooks influences girls' achievement in STEM activities will increase children's likelihood of attributing gender disparities in STEM achievement to structural factors. Grounded in social identity and stereotype threat theories, such exposure helps children view gender disparities as societal barriers rather than personal limitations, reducing stereotype threat and fostering belonging (Kim et al., 2018; Master, 2021). Alternatively, if no effect is found, it may suggest that representation alone is insufficient and that additional factors, such as direct interactions, long-term exposure, or explicit discussions, are needed to challenge stereotypes and promote structural reasoning.

Method

Participants

The study will recruit 96 girls aged 5–8 from a university infant database. This sample size and age range were chosen based on a prior study, which investigated children's structural reasoning and demonstrated that structural reasoning begins developing around age 5 (Amemiya & Bian, 2024).

Procedure

Participants will be tested via Zoom, using Qualtrics surveys. Each participant will receive a $5 Amazon gift card as compensation.

Children will be presented with two hypothetical scenarios involving competitions in a fictional town: a robot-building competition and a puzzle-solving competition. First, children will be randomly assigned to one of three conditions in the robot-building scenario: baseline, within, or between conditions. In all conditions, participants will be told that children in the scenario read a textbook on robot building and participate in a robot-building competition spanning four hypothetical years. In the baseline condition, the textbook will not feature any specific scientists, and boys will win the competition in all years. In the within condition, the textbook will feature female scientists for the first two years and male scientists for the last two years, with winners' genders corresponding to the gender of the scientists. In the between condition, the textbook will feature male scientists across all four years, with boys winning each year. A condition featuring only female scientists will not be included because, in all conditions, children will be asked to reason why girls are underrepresented in STEM activities, requiring at least one year where boys win. This design also reflects reality, as most scientists children hear about are male. The goal is to test whether children can identify this lack of female scientists as a structural barrier for girls. Then, the puzzle-solving competition, included as a baseline condition, will be presented to children to assess whether they can generalize their structural reasoning to another context or not.

After each scenario, open-ended questions will prompt them to explain why no girls won in the last year, and closed-ended questions will ask them to evaluate intrinsic, random, and structural explanations provided by fictional characters as accurate or inaccurate.

Results

Descriptive Statistics

Table 1

Summary statistics for a numeric variable (Age)

Total count	Mean	Standard Deviation	Minimum	Maximum	Median
65	6.42	1.14	5.00	8.00	6.00

The dataset includes 65 participants, with ages ranging from 5 to 8 years. The average age of participants is 6.42 years (SD = 1.14), and the median age is 6 years. See Table 1 for a full summary of the data.

Table 2

Summary statistics for a non-numeric variable (Condition)

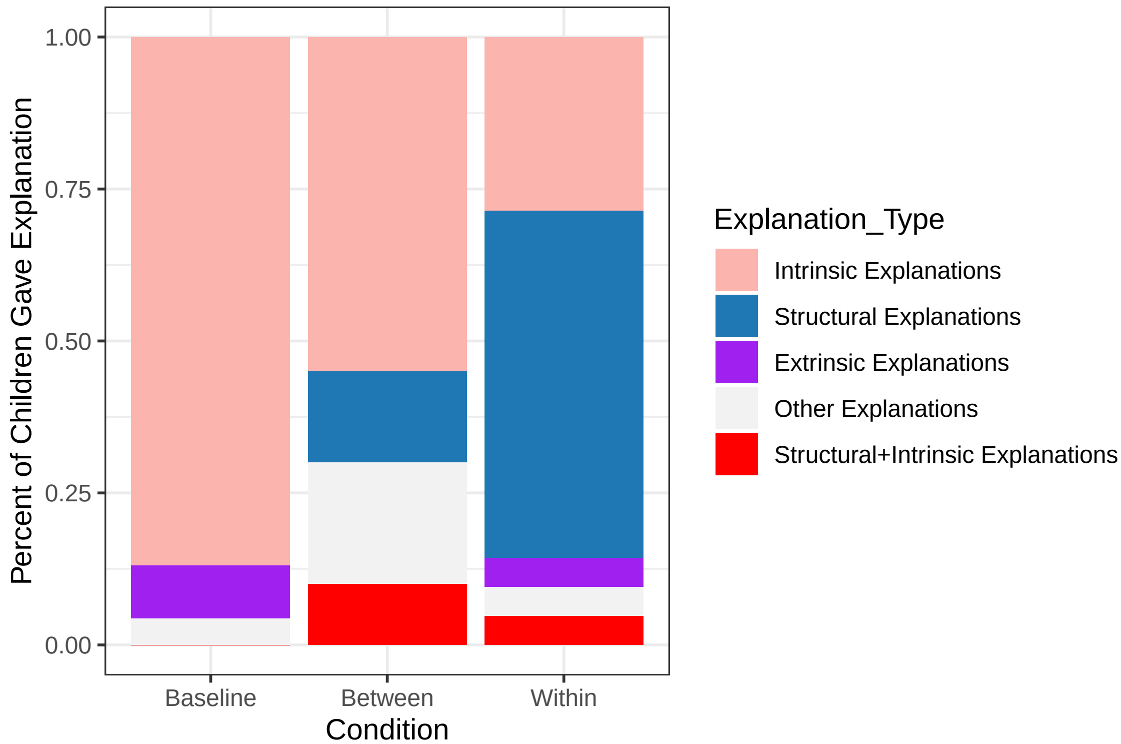
Condition	Count	Proportion (%)
Baseline	24	36.92
Between	20	30.77
Within	21	32.31

The dataset includes 65 participants. In the Baseline condition, 24 participants were included, making up 36.92% of the sample. In the Between condition, 20 participants were included, representing 30.77% of the total sample. Finally, in the Within condition, 21 participants were included, comprising 32.31% of the dataset. See Table 2 for a full summary of the data.

Robot Building Open-ended Questions

Figure 1

Robot Building Open-Ended Explanations: Explanation Types by Condition



Note. Stacked bar chart displaying the percentage of children providing each type of explanation across three experimental conditions: Baseline, Between, and Within. The y-axis represents the proportion of children giving each explanation type, while the x-axis represents the experimental condition. Explanation types are color-coded as follows: Intrinsic (pink), Structural (blue), Extrinsic (purple), Other (light gray), and Structural+Intrinsic (red).

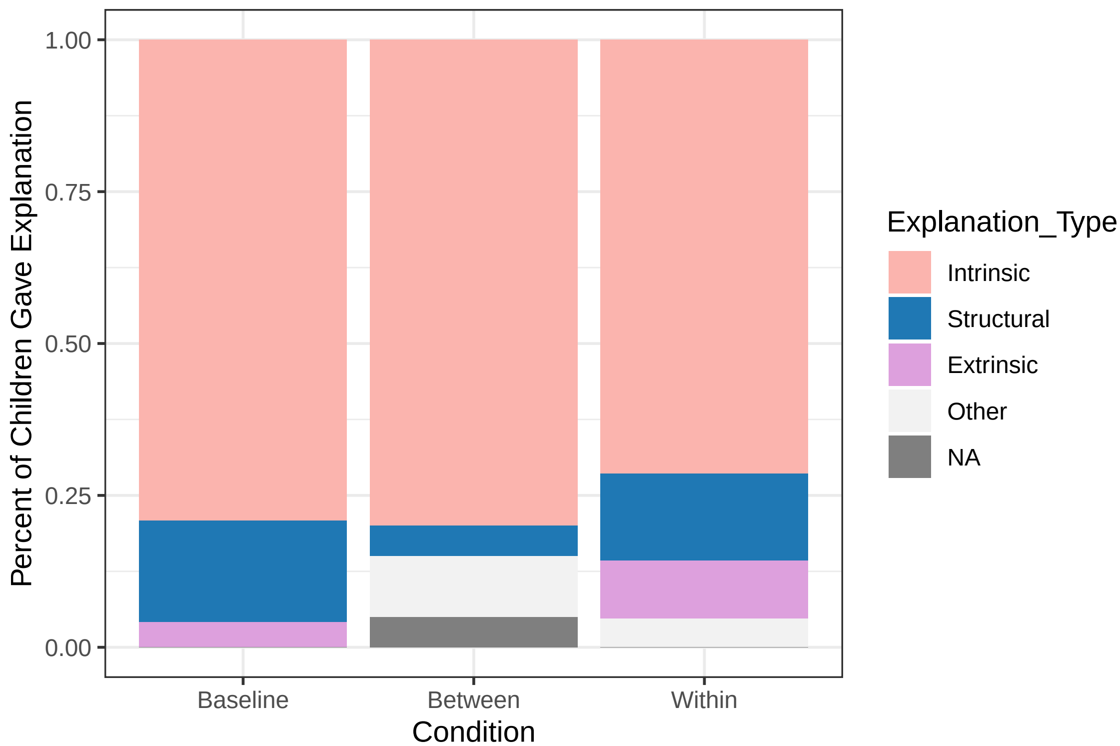
The Chi-Square test for condition and open-ended questions in the robot-building scenario showed a significant results, $\chi^2(8) = 30.2$, $p = 0.000$, indicating that participants' responses in the robot open-ended category varied significantly across conditions.

As illustrated in Figure 1, children in the Baseline condition predominantly provided intrinsic explanations. Intrinsic explanations decrease in the Between and Within conditions, particularly in the Within condition. Structural explanations are present in the Between condition and show a substantial increase in the Within condition. This pattern suggests that exposure to structural information in the Between and Within conditions influenced children's reasoning, leading them to attribute outcomes to structural factors rather than intrinsic ones. Furthermore, the Within condition appears to be more effective in increasing structural explanations.

Puzzle Solving Open-ended Questions

Figure 2

Puzzle Solving Open-Ended Explanations: Explanation Types by Condition



Note. Stacked bar chart displaying the percentage of children providing each type of explanation across three experimental conditions: Baseline, Between, and Within. The y-axis represents the proportion of children giving each explanation type, while the x-axis represents the experimental condition. Explanation types are color-coded as follows: Intrinsic (pink), Structural (blue), Extrinsic (purple), Other (light gray), and NA (dark gray).

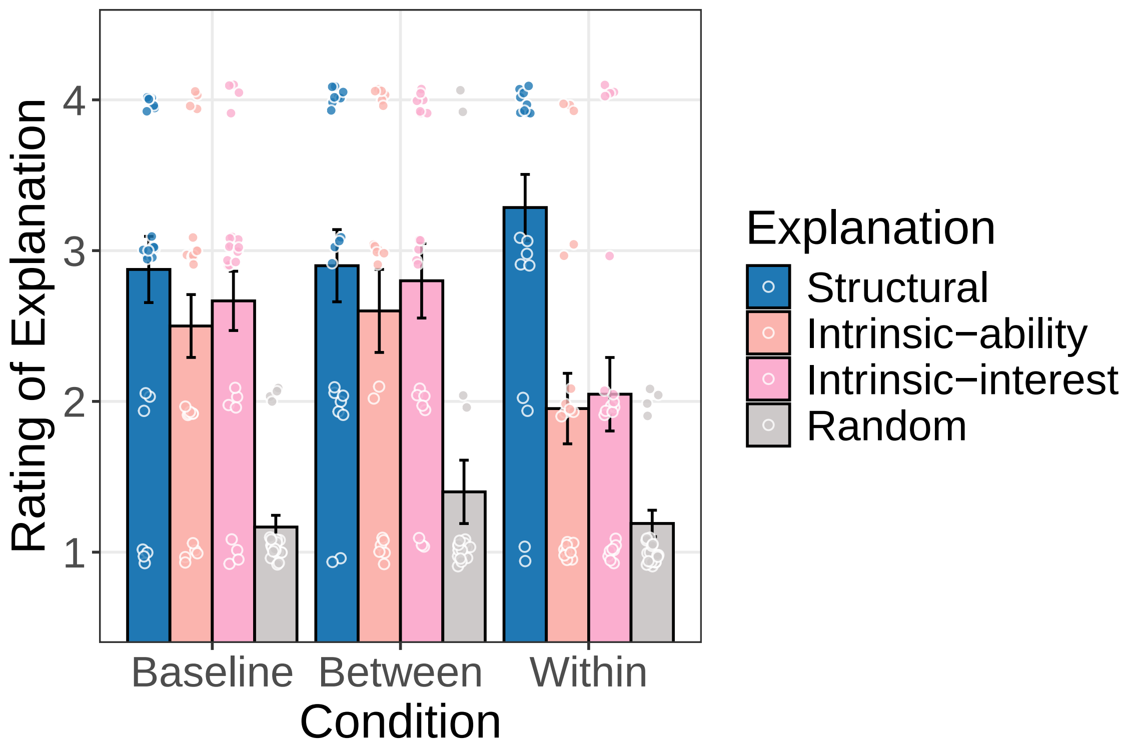
In contrast, the Chi-Square test for condition and open-ended questions for the puzzle-solving scenario did not show significant results, $\chi^2(8) = 8.07$, $p = 0.426$, indicating that responses in the puzzle open-ended category were not significantly different across conditions.

As illustrated in Figure 2, children do not appear to generalize their reasoning from the robot-building task to the puzzle-solving domain. Intrinsic Explanations remain the most common across all conditions, and structural explanations are present in all conditions.

Robot Building Closed-ended Questions

Figure 3

Robot Building Close-Ended Explanations: Explanation Types by Condition



Note. Bar graph displaying the mean rating of explanations provided by children across three experimental conditions: Baseline, Between, and Within. The y-axis represents the mean rating of each explanation type, while the x-axis represents the experimental condition. Error bars indicate standard errors. Explanation types are color-coded as follows: Structural (blue), Intrinsic-ability (pink), Intrinsic-interest (light pink), and Random (gray).

The linear regression analyses for the robot-building closed-ended questions indicated no significant differences across conditions in children's explanations. For structural explanations, the model did not show a significant effect of condition, $\beta = 0.02$, $SE = 0.32$, $t(62) = 0.08$, $p = 0.938$, suggesting that ratings of structural explanations did not significantly differ in the Within condition. For ability explanations, the Within condition also did not show a significant effect, $\beta = 0.1$, $SE = 0.33$, $t(62) = 0.3$, $p = 0.766$. For interest explanations, there was a nonsignificant trend in the Within condition, $\beta = 0.13$, $SE = 0.32$, $t(62) = 0.42$, $p = 0.679$, indicating a potential trend toward lower interest ratings in the Within condition, though it did not reach statistical significance.

As illustrated in Figure 3, the Within condition showed a slight increase in structural explanations compared to Baseline and Between conditions, but this effect was not statistically significant. Ratings of intrinsic-ability and intrinsic-interest explanations decreased in the Within condition, though it did not reach statistical significance.

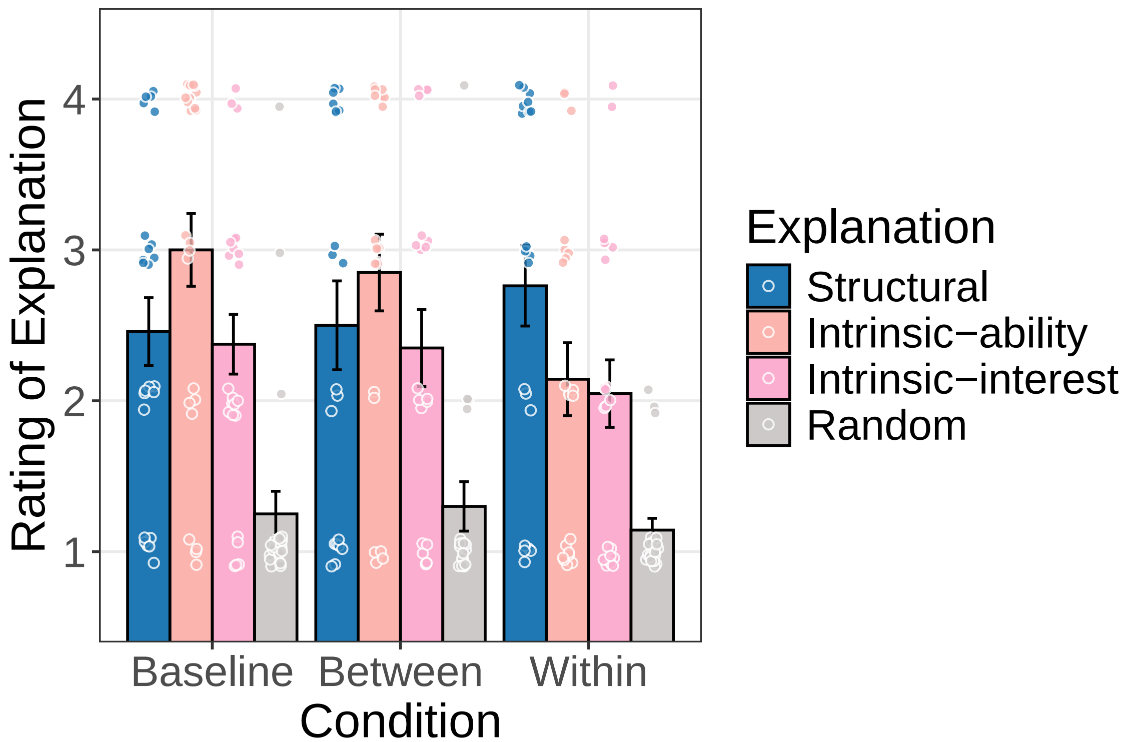
Puzzle Solving Closed-ended Questions

The linear regression analyses for the puzzle-solving closed-ended questions indicated no significant differences across conditions in children's explanations. For structural explanations, the model did not show a significant effect of condition, $\beta = 0.04$, $SE = 0.37$, $t(62) = 0.11$, $p = 0.910$, suggesting that ratings of structural explanations did not significantly differ in the Within condition. For intrinsic-ability explanations, the Within condition also did not show a significant effect, $\beta = -0.15$, $SE = 0.35$, $t(62) = -0.43$, $p = 0.666$. For intrinsic-interest explanations, there was a nonsignificant trend in the Within condition, $\beta = -0.02$, $SE = 0.32$, $t(62) = -0.08$, $p = 0.937$, indicating a potential trend toward lower intrinsic-interest ratings in the Within condition, though it did not reach statistical significance.

As illustrated in Figure 4, structural explanations slightly increase in the Within condition compared to the Baseline and Between conditions, while intrinsic-ability and intrinsic-interest explanations show a slight decrease in the Within condition compared to the Baseline and Between conditions. However, these differences were not statistically significant. The overall pattern of explanation types appears similar to the robot-building scenario.

Figure 4

Puzzle Solving Close-Ended Explanations: Explanation Types by Condition



Note. Bar graph displaying the mean rating of explanations provided by children across three experimental conditions: Baseline, Between, and Within. The y-axis represents the mean rating of each explanation type, while the x-axis represents the experimental condition. Error bars indicate standard errors. Explanation types are color-coded as follows: Structural (blue), Intrinsic-ability (pink), Intrinsic-interest (light pink), and Random (gray).

Discussion

For the robot-building task, the significant effect in the open-ended responses indicates that children adjusted their explanations based on the condition. The increase in structural explanations in the Within condition suggests that exposure to structural information influenced children's reasoning, encouraging them to shift away from intrinsic explanations. In contrast, the puzzle-solving task did not show significant differences in open-ended responses across conditions, suggesting that children may not generalize structural reasoning from one domain to another. However, the finding that interest explanations showed a marginal effect in the Within condition suggests some potential for influence, even if the effect was not statistically significant.

The close-ended responses for both the robot and puzzle tasks showed patterns consistent with the open-ended results. While structural explanations increased slightly in the Within condition and intrinsic explanations decreased, these changes were not statistically significant. The similarity in patterns between open- and close-ended responses suggests that the influence of structural information may be emerging but is not yet strong enough to produce consistent effects across domains or response types. The lack of significant effects in the puzzle task indicates that generalization across domains may require stronger or more consistent exposure to structural cues.

Additionally, structural explanations were present in the puzzle-solving scenario for the open-ended questions, which were always presented in the Baseline condition. This raises potential methodological concerns. Since all participants engaged in close-ended questions about robot-building—which included structural explanations—before completing the puzzle-solving scenario, it is possible that children recalled these structural explanations and reused them when responding to subsequent questions. This could be a limitation in the study design, as prior exposure to structural reasoning may have influenced children's responses across conditions.

In sum, this research addresses a critical gap in the literature by examining how exposure to representations of female scientists in educational materials shapes children's reasoning about gender disparities in STEM achievements—a topic that, to my knowledge, has not been explored. These findings suggest that structural reasoning can be facilitated through targeted exposure to structural information, but such effects may be task-specific. Future interventions aimed at promoting structural reasoning in educational settings should consider the relevance of the task and the consistency of the cues provided. By shedding light on how children's reasoning about these disparities can be influenced, this study offers valuable insights for fostering a more equitable future in STEM fields.

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Appendix

I created 5 code chunks that are not necessarily related to the final report; however, these chunks demonstrate **Learning Objectives**: *6,8,11,15,27*. The two graphs, Figure A1 and Figure A2, presented below are the graphs created using facet_wrap and facet_grid, achieving LO: 15.[1]

- **Learning Objectives:**
  - 6: Use arithmetic, comparison, and logical operators
  - 8: Parse and write conditional statements and/or loops
  - 11: Use `stringr` functions to work with string variables
  - 15: Use facets to create parallel plots
  - 27: Use quarto R Markdown to compose an academic manuscript

[1] Demonstration of LO 6, 8, and 11 can be found in the Structural Thinking.qmd file in the code chunks: Str(), Operators, and Conditional-statements.

Figure A1

Age Distribution by Condition

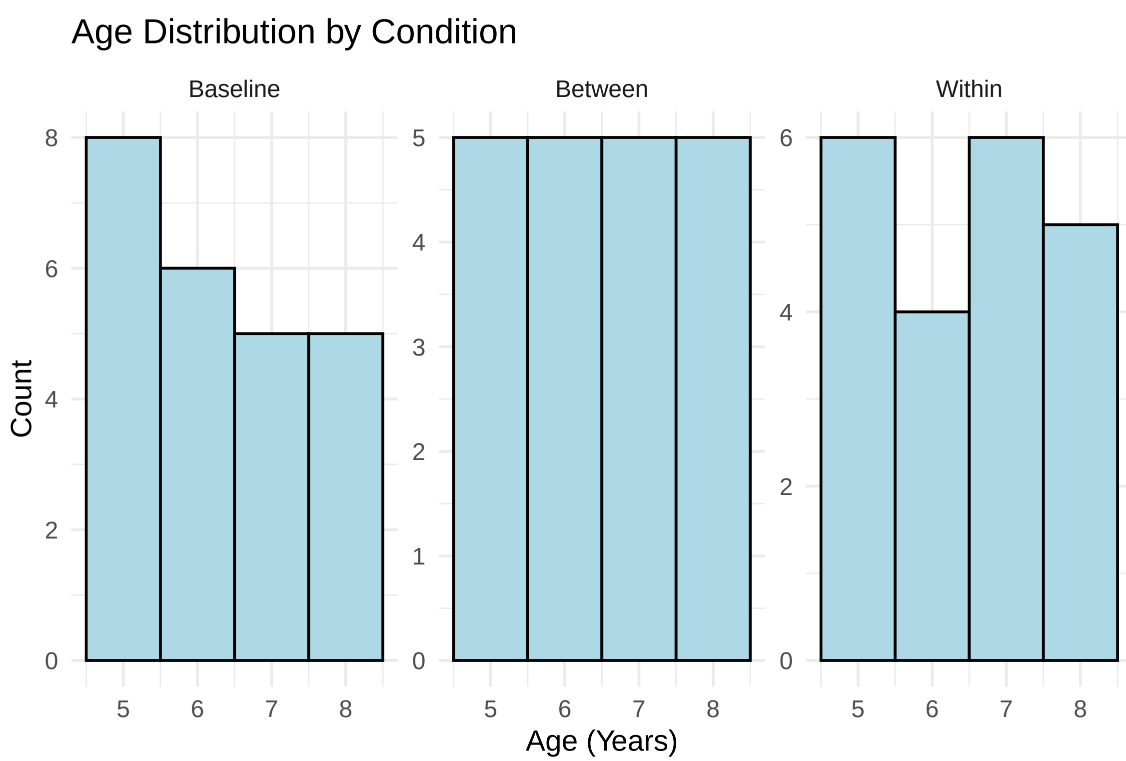

Figure A2

Age Distribution by Condition and Gender