

Access to Educational Robotics is Linked to Socioeconomic Status: A Correlational Analysis

Paarth Jain¹ and Margaret Donhauser[#]

¹Hunterdon Central High School, USA

[#]Advisor

ABSTRACT

The study investigates the relationship between a region's average socioeconomic status (SES) and the accessibility of educational robotics (ER) in that region. The study sampled 120 regions of varying SES across NJ to examine the presence of robotics education for high school students. Then, a correlational analysis was conducted, revealing a relationship between the SES of a region and the accessibility of ER. As SES increases, the accessibility of ER also increases among high schools. The study's findings play a role in promoting a more equal STEM landscape, across both education and the workforce. ER is a tool that can be used to provide an integrated STEM education, and, therefore promote both STEM skills and interest. With lower SES regions not having access to ER, students from those backgrounds do not have the same opportunities to enhance their STEM skills and interests. These findings can be used by both policymakers and educational organizations in an effort to make the landscape of STEM education and ER more equal. As that happens, an increase in diversity of the STEM field can be expected.

Access to Educational Robotics is Linked to Socioeconomic Status: A Correlational Analysis

Over the last few decades, the world has witnessed a technological revolution that has changed everyday life. With the onset of technology, the STEM, or the science, technology, engineering, and math sector, of the workforce has grown rapidly. According to the U.S National Science Foundation, from 2011 to 2021, occupations in the STEM field have increased from 22.9 million to 34.1 million jobs. The field, however, has a lack of diversity, which has not decreased despite the uptick in jobs. According to the same report, Black or African Americans comprised only 9% of STEM jobs in 2021. Similarly, other minority groups, such as Hispanic workers, are severely underrepresented in the field (US National Science Foundation, 2023).

According to Cathy Hall et al. (2011), one leading cause of the inequality in the STEM field is a lack of STEM education for underrepresented populations. Her study found that support through the educational system is crucial for encouraging minority students to embark upon STEM careers. This point of view was further corroborated by a study conducted by Svetlana Chachashvili-Bolotin et al. (2016), who determined that STEM education and learning experiences increase the interest in students pursuing STEM fields. These findings support the conclusion that STEM education, or lack thereof, is crucial to the current lack of diversity in the field. Therefore, to improve the current state of diversity in the STEM field, STEM education must be improved.

STEM education is a term for education in the disciplines of science, technology, engineering, and math. The term STEM education changes throughout the field, with two main definitions. The first one defines STEM education as a broad category of disciplines that can be dealt with individually, whereas the second

primary definition defines STEM education as the interdisciplinary study of the four disciplines in which an integrated approach to education is taken (Martín-Páez et al., 2019). This paper will define STEM education using the second definition, an interdisciplinary approach to education that integrates concepts of all four disciplines.

Literature Review

Educational Robotics (ER)

Educational Robotics (ER) is an interdisciplinary method of STEM education in which robots are used to convey educational concepts (Angel-Fernandez & Vincze, 2018). Educational robotics is rooted in the foundational theory of constructivism, which states that students construct knowledge rather than passively intaking it (Peter Ngugi Mwangi et al., 2022). A successful educational robotics program is built around a student framework in which the students learn to “design and adapt,” “implement,” “evaluate and assess,” and “improve” their robots (p. 2). This framework utilizes the theory of constructivism and an interdisciplinary approach to STEM education to maximize student benefits (Angel-Fernandez & Vincze, 2018).

Benefits of Educational Robotics

As an interdisciplinary STEM education approach, ER provides the many benefits of STEM education in a single subject course.

Benefits to STEM Skills

Educational robotics has been shown to positively impact the acquisition of STEM skills. Using ER, Ziaeeafard et al. (2017) present an approach to engineering design education and measure the effectiveness of ER in promoting STEM skills in students. They find that using ER sustains high school student engagement in STEM and promotes the development of STEM skills. Similarly, Kim et al. (2015) conducted a study to explore the impact of educational robotics on teachers' views on STEM education. The study found that, like researchers, teachers believed ER to be highly effective in conveying STEM skills. This view was also supported by high school students, who, through surveys by Negrini and Giang (2019), reported that ER improves their STEM skills. Across the different perspectives, ER is well regarded as a tool for improving STEM skills.

Benefits to Computational Thinking Skills

Computational thinking (CT) is defined as the ability to formulate algorithmic solutions to problems. It has been shown to positively impact the acquisition of STEM skills. In an experimental study, Francisco José García-Peñalvo et al. (2020) measured the acquisition of STEM skills and CT in high school students. They found that ER was influential in introducing CT and supported the development of STEM skills, corroborating research by Ziaeeafard et al. (2017) and Kim et al. (2015). This conclusion is supported by the perspective of high school students, who reported through surveys that they believe ER improved their CT skills (Negrini & Giang, 2019).

Overall, ER develops both STEM and CT skills, which is valuable for students pursuing careers in the STEM field.

STEM Learning Motivation and Interest

The use of robotics in STEM education has been shown to positively impact high school students' interest in pursuing STEM studies and STEM-related careers. Hendricks et al. (2020) found that participation in robotics

competitions promoted high school students' interest in the STEM field. Similarly, in their study to investigate the effects of ER on STEM interest, Khanlari et al. (2013) found that using educational robots positively attitudes toward STEM. The findings of both studies suggest that ER can positively impact students' attitudes toward STEM and thereby increase their interest in STEM careers. The increased interest and better attitude towards STEM make ER an effective tool for promoting diversity in the STEM field.

ER as a Tool to Increase Diversity in STEM Fields

The acquisition of STEM skills and interest in STEM promoted through ER makes ER a valuable tool for fostering diversity in the STEM field. According to a literature review by Lisa Tsui (2007), numerous research studies suggest that STEM education programs best serve underrepresented communities if they are an integrated STEM approach. Daniela and Lytras (2018) apply this view to ER, as they identified educational robotics to be a medium through which STEM education can be provided inclusively between races and genders. They argue that since ER robotics is an integrated STEM approach, it can serve underrepresented communities and work to heal the lack of diversity in the STEM field.

However, ER cannot remediate the lack of diversity in STEM fields unless it is equitably available.

Research, such as a study by Wallace and Populus (2022) and an editorial by Daniela and Lytras (2018), describes ways to improve equitable access to ER, indicating that access to ER is inequitable. Both works, however, fail to identify where the inequity in robotics education occurs. Wallace and Populus (2022) suggest that the access gap may be between socioeconomic classes, yet they do not provide definitive data to prove that claim. Data that clearly defines where the inequality in access to ER exists is missing from the field. Therefore, research on the accessibility of robotics education is needed to determine where this inequality occurs. This gap leads to the research question: Is there a correlation between a region's socioeconomic status and the access to robotics education within that region for high school students in New Jersey? This research question looks to identify where this inequality occurs through the lens of socioeconomic status. The population of the research question is limited to high school students because the benefits attributed to ER are primarily found at the high school level, and the interest ER provides in the STEM field is the most valuable to high school students.

Socioeconomic Status as a Measure of Inequality

Socioeconomic status (SES) is a standard measure used to research educational inequality. It was invented to measure the combined effects of several variables, including parent income, educational attainment, and job-status, on student performance (National Center for Education Statistics, 2013, p. 12). Since then, SES has become the standard measure for reporting educational inequality since it considers a multidimensional view of the factors behind it (Oakes, 2006, p. 14). This study aims to identify where the inequality in access to ER exists. Several studies with similar goals of identifying where an educational inequality exists, such as Kennedy (2015), Kliucharev and Kofanova (2005), and Walpole (2003), all use SES rather than a single variable such as race, gender, or income, to measure inequality in access to their respective aspects of education. Therefore, this paper investigates access to ER through the lens of socioeconomic status to determine where inequality exists.

Conclusion

Since access to this education is unequal, its benefits are also unequal. This research will provide foundational information for other researchers and educational organizations to explore and eliminate ER inequality by identifying exactly where it exists. Moreover, the results of this study can be used as a base for other researchers

who look to further identify the causes of inequality or propose solutions to reduce this inequality.

Methods

The research question investigates the correlation between socioeconomic status and access to robotics education. As such, a correlational analysis, which investigates the relationship between two or more variables to determine whether the variables have a defined relationship, is an appropriate method for this study. Correlational studies investigate phenomena that have already occurred, meaning the researcher does not control or manipulate any variables. This allows the findings of correlational research to be more applicable to the real world (Simon & Goes, 2011, p.1). The goal of this research is to investigate a preexisting phenomenon: the correlation between access to ER and SES; therefore, correlational analysis works well.

The method takes four steps: 1) Classification of SES of Regions in NJ, 2) Sample Selection, 3) Data Collection, and 4) Correlational Analysis.

Classification of SES of Regions

The first step of the method was to split NJ into regions with different socioeconomic classifications. Every study classifies SES slightly differently, factoring in different variables to best match their research goals (National Center for Education Statistics, 2013, p. 12). For example, Dotson et al. (2009) classified the SES of individuals based solely on their median income, while Broer et al. (2019) classified the SES of individuals based on three educational factors: the number of books at home, the number of home possessions, and the highest level of education of either parent.

The researcher had two options when developing a scale for SES: develop a scale to classify SES explicitly designed for the research or use a preexisting scale in the field. Classification of SES of the regions in NJ is an integral part of the research goal; therefore, the researcher chose to use a preexisting scale to ensure validity. The research question looks at the SES status of regions in NJ from the lens of access to education; therefore, the SES scale needed for this research must have classified the SES of regions, not individuals, and focused on classifying SES based on educational factors.

The SES scale that best fits these measures was developed by the New Jersey Department of Education (NJDOE) in 1990. The “District Factor Groups” (DFGs) scale broke NJ by school district into 555 regions. Each region was classified as one of eight SES groups: A, B, CD, DE, FG, GH, I, and J, with “A” being the lowest SES classification and J being the highest. The SES classifications were based on the following six variables related to education: percent of adults with no high school diploma, percent of adults with some college education, occupational status, unemployment rate, percentage of individuals in poverty, and median family income (New Jersey Department of Education, 1990). The DFGs were updated in 2017 by the Education Law Center, and the updated classifications are used in this study (Education Law Center, 2017).

The DFG system was an optimal choice for an SES classification method because it met all the requirements for this study. It classified SES by region rather than individual, prioritized educational-based factors, and was recently updated. Moreover, the system is created by the NJDOE, providing additional validity to this study’s method and potentially allowing the research findings to be more readily applicable to public policy.

Sample Selection

New Jersey was chosen as the sample for this study because it is largely representative of the United States in terms of the factors used to classify SES and educational attainment. Therefore, the findings of this study could

potentially be generalized to the larger US population. Table 1 compares the United States and NJ regarding the six factors used to classify SES in this study.

Table 1, New Jersey and the United States in Several SES Determining Factors

SES Determining Factor	NJ Average	US Average
Percent of adults with no high school diploma	11%	11.6%
Percent of adults with some college education	38.7%	39.6%
Unemployment rate	8.9%	6.8%
Percent of individuals in poverty	6.8%	8.9%
Median family income	\$96,000	\$75,000

Note. The data from the table above is from the American Community Survey by the US Census Bureau (2022). Data on occupational status was unavailable and, therefore, omitted from the table. Occupational status is not a metric through which NJ and the US can be compared since it is not a quantitative variable.

Table 1 demonstrates that, except for median family income, NJ is largely representative of the United States in terms of the factors used to classify SES in this study. As a result, this study's sample was designed to represent the entire population of NJ, potentially allowing for the findings of this study to apply to the larger US population.

The researcher identified the sample size through a sample size calculator. Based on the DFGs, NJ was split into 555 regions. The researcher chose to sample 120 of these regions to account for a 90% accuracy and $\pm 6\%$ margin of error of all NJ regions. This accuracy rate and margin of error were chosen primarily due to time constraints, as 95% and 99% confidence intervals would have resulted in samples that would be too large to collect data for. Table 2 details the sample chosen.

Table 2. Regions in New Jersey and Sample

SES Group	Number of Regions in NJ	Percent of Regions in NJ	Number of Regions Sampled	Percent of Regions of Sample
A	29	5.2%	6	5.2%
B	50	9%	11	9%
CD	80	14.4%	17	14.4%
DE	111	20%	24	20%
FG	101	18.2%	22	18.2%
GH	76	13.7%	16	13.7%
I	83	14.9%	18	14.9%
J	25	4.5%	5	4.5%
Total	555	$\cong 100\%$	$\cong 120$	$\cong 100\%$

Note. The number of regions sampled was based on the percent of regions in NJ (divided by 100) * total number of regions in NJ and rounded to the nearest whole number. Total regions may not add up to 120 due to rounding errors.

Table 2 shows that some SES groups had more regions than others in the NJ population. To make the sample as representative of NJ as possible, the researcher took the percentage of regions of each SES group and matched that percentage breakdown in the 120-region sample. The number of regions per SES group sampled is also displayed in Table 2. The specific regions sampled within each SES group were selected at random.

Data Collection

The definition of access to ER could take many forms. One definition of access to education is the presence of education that a student can partake in (Bhalla, 1992). Based on this, access to ER is defined in this study as the presence of an ER program within a student's region. This definition best fills the gap since both Wallace and Populus (2022) and Daniela and Lytras (2018) define access to ER as the presence of an ER program in which students can participate. Further, the researcher can easily measure the presence of an ER program in a region.

Data was collected on the presence of the four main types of ER: Robotics classes in school, robotics clubs in school, free robotics classes/clubs outside school, and paid robotics classes/clubs outside school. These four variables encompass almost all forms of ER, and therefore, by selecting these variables, the researcher accounted for all forms of ER that could be present. The steps conducted for collecting data on those four variables are as follows:

1. Through a Google search, the researcher found the website of the high school in each region. Once on the website, the researcher navigated to the program of studies (or similar course catalog) to check for any robotics courses available to students. If a high school offers a robotics education program, a yes was marked in the "in-school robotics education class" column on the data collection spreadsheet.
2. Next, the researcher located the high school's list of clubs on their website. If the high school has a robotics club/team, a yes was marked in the "in-school robotics education clubs" column on the data collection spreadsheet. A list of high schools used for data collection is available in Appendix B.
3. Next, the researcher checked the FIRST team database (FIRST, 2024) and searched for a team in each region. FIRST is an organization that hosts a majority of high school-level ER competitions; therefore, checking FIRST databases was a logical step. If a FIRST high school team exists, a yes was marked under "Outside School, Free Robotics Education Program."
4. The researcher then conducted a Google search using the name of the region and the keywords: "robotics program"/ "robotics team" / "robotics class" + "for kids"/ "for high schoolers" / "for students." All combinations of the search terms were used. If a free robotics program were available within the school district's boundaries, a yes was marked under "outside school, free robotics education program." If the robotics program is not free, a yes was marked under "outside school, paid robotics education program."
5. Finally, the total number of programs found in each region was recorded in the column "Total Number Robotics Programs." An example of a spreadsheet used to collect the data is available in Appendix A.

For robotics education programs outside school, the researcher will only consider programs within the region's boundary, as classified by the NJDOE (State of New Jersey, 2022), to ensure no overlap between regions. In addition, the researcher will only consider programs available to high school students.

Survey research was considered for data collection. However, due to time constraints, survey research may not have reached an adequate response rate to allow the researcher to generalize the findings in the way the researcher can with the method chosen. Moreover, it is possible that potential respondents were unaware of the robotics education programs available in their region. This would have skewed the data responses and

made it unclear whether a robotics education program exists in that region. Due to these factors, the data collection method described was decided.

Correlational Analysis

Once all the data was collected, correlational analysis was applied to determine the correlation between the access to ER and SES. Access to ER was defined as the presence of one ER program in a region. The researcher determined which regions in an SES group had access to ER based on this definition, where any region with at least one “yes” in any of the four categories was counted as having access to ER. The number of regions with access to ER in each SES group was totaled, and a percentage of the regions with access to ER was calculated.

To conduct correlational analysis, the Pearson Correlation coefficient was used to compare the percentage of regions in each group with access to ER and SES. The Pearson Correlation Coefficient equation returns an R-value between -1 and 1, indicating the strength of the relationship between the two variables. Though other statistical tests, such as the Chi-Square, were considered for this research, the Pearson Correlation Coefficient was chosen because it returns the strength and direction of the relationship between the variables (Schober et al., 2018). The R-value returned by the test was analyzed using the measures in Table 3.

Table 3. Analysis of the R-value returned by the Pearson Correlation Coefficient Test

Returned R-Value	Analysis
Between -0.9 and -1	Very Strong, Negative Correlation
Between -0.7 and -0.89	Strong, Negative Correlation
Between -0.4 and -0.69	Moderate, Negative Correlation
Between -0.1 and -0.39	Weak, Negative Correlation
Between 0.1 and -0.1	No Correlation
Between 0.1 and 0.39	Weak, Positive Correlation
Between 0.4 and 0.69	Moderate, Positive Correlation
Between 0.7 and 0.89	Strong, Positive Correlation
Between 0.9 and 1	Very Strong, Positive Correlation

Note. The scale above was developed based on Schober et al. (2018).

The Pearson Correlation Coefficient Test was conducted by first coding the qualitative SES groups (A through J) into numerical variables, with the lowest SES group, “A,” receiving a value of one and each group above it receiving a corresponding number (e.g., B → 2, CD → 3, etc.). Then, the correlation coefficient test was applied using Google Sheets, comparing the percent of regions with access to ER with their respective socioeconomic statuses. The percentage of regions with access to ER was used to compare SES groups, rather than the number of regions with access to ER, because each SES group did not have the same number of regions. The formula used for this and the Google Sheet on which it was conducted can be found in Appendix C.

Limitations

Conducting a correlational study has limitations that must be addressed. Correlational research cannot determine the causes of low access to robotics education or a corresponding inequality, as correlational analysis only determines relationships between variables, not causation. However, my research question does not seek to uncover the cause of the lack of access to robotics education in a region. Instead, it seeks to identify patterns in certain regions with low access to robotics education, which could lead future researchers to examine the causation.

Correlational analysis works optimally to meet this goal.

Results

To determine whether students in a sample SES group had access to robotics education, data was collected on four variables: the presence of robotics classes in the high school in the regions of that group, the presence of a robotics club/team in the high school in the regions of that group, the presence of free robotics programs/classes in the regions of that group, and the presence of paid robotics programs/classes in the regions of that group. A correlational analysis test was conducted on the overall access to educational robotics in relation to SES to examine the relationship between the variables. The results of the data collected and the correlational analysis are presented in the following section.

Table 4 describes the number of in-school robotics classes within each SES group sample. Since the number of regions in each SES group differs, the percentage of regions with robotics classes was used to compare the relationship between SES groups and the presence of robotics classes.

Table 4. Presence of In-School Robotics Classes within SES Groups

SES Group	# of Regions Sampled within Group	# of Regions with In-School Robotics Classes in each Group	% of Regions in Group with In-School Robotics Classes
A	6	2	33.3%
B	11	4	36.36%
CD	17	8	47.0%
DE	24	14	58.3%
FG	22	12	54.5%
GH	16	10	62.5%
I	18	15	83.33%
J	5	4	80%

Within the sample, the percentage of regions with robotics classes in their high schools demonstrates an upward trend compared to increasing SES, indicating that more regions in school have robotics classes in higher SES groups.

Table 5 reports the number of robotics clubs in high schools within each SES group sample.

Table 5. Presence of In-School Robotics Clubs within SES Groups

SES Group	# of Regions Sampled within Group	# of Regions with In-School Robotics Clubs in each Group	% of Regions in Group with In-School Robotics Clubs
A	6	3	50%
B	11	2	18.8%
CD	17	8	47.0%
DE	24	14	33.3%
FG	22	12	45.4%
GH	16	8	50%
I	18	10	55.5%
J	5	5	100%

Similar to in-school robotics classes, the data in Table 5 demonstrates an upward trend where more high schools have a robotics club present in higher SES groups.

Table 6 reports the presence of outside-school free and paid robotics education programs in the samples of the SES groups. These programs could be robotics clubs, teams, or classes, but they are all programs not affiliated with the high school in the region.

Table 6. Presence of Free and Paid Robotics Programs Within SES Groups

SES Group	# of Regions Sampled	# of Regions with Free Robotics Programs Outside of School	% of Regions with Robotics Free Programs Outside School	# of Regions with Paid Robotics Programs Outside of School	% of Regions with Robotics Paid Programs Outside School
A	6	0	0%	0	0%
B	11	1	9%	1	9%
CD	17	0	0%	1	5.8%
DE	24	2	8.3%	2	8.3%
FG	22	1	4.5%	1	4.5%
GH	16	1	6.25%	1	6.25%
I	18	0	0%	0	0%
J	5	0	0%	1	0%

Unlike Tables 4 and 5, the data in Table 6 shows no apparent trend between SES and the presence of a free or paid robotics education program outside each school.

In this study, the term “access” to robotics education refers to the presence of just one ER program in a region because it allows students in that region to participate in robotics education. A region was considered to have access to ER if it had one of the following types of ER programs: In-School Robotics Classes, In-School Robotics Clubs, Outside-School Free ER Programs, or Outside-School Paid ER programs. Table 7

reports the number and percent of regions in the various SES groups where students have access to robotics education.

Table 7. Access to Robotics Education in Sample

SES Group	# of Regions Sampled	# of Regions with Access to Robotics Education	% of Regions with Access to Robotics Education
A	6	3	50%
B	11	7	63.3%
CD	17	13	76.4%
DE	24	19	79.1%
FG	22	17	77.2%
GH	16	13	81.25%
I	18	16	88.8%
J	5	5	100%

The percentage of regions with access to robotics education is used to compare with various groups.

A correlational analysis was conducted on the percentage of regions with access to ER in each SES group and SES. When the analysis was conducted, the coefficient R equaled 0.91, indicating a very strong, positive relationship between increasing SES and increasing access to ER. Therefore, the data shows that as SES increases, the percentage of students with access to ER increases concurrently.

Finally, the average number of ER program options available to students in each group was recorded. This average was calculated by totaling the number of ER programs available (across all four groups) in a region and dividing that by the number of regions with access to at least one program. Table 8 displays the average number of “options” students had within each region.

Table 8. Average Number of ER Program Options for Students

SES Group	Average # of Options of ER Programs
A	1.50
B	1.14
CD	1.30
DE	1.15
FG	1.29
GH	1.38
I	1.68

The trend in Table 8 indicates that the average number of options a student has for an ER program increases as SES increases.

Discussion

The purpose of this study is to determine if there is a correlation between SES and access to robotics education for high school students in NJ. Prior research, such as a study conducted by Wallace and Populus (2022) and Daniela and Lytras (2018), acknowledges an inherent inequality in access to robotics education. Yet, the current information in the field does not identify where this inequality exists.

This study's results indicate a significant positive correlation between access to ER and SES. As SES increases, the percentage of high school students with access to ER also increases. This is shown in Table 7, where as the SES increases from the lowest group (A) to the highest group (J), the percentage of students with access to ER also increases. The correlational value of 0.917 indicates a strong positive relationship between the accessibility of ER and SES. These findings identify a pattern to where the inequality in access to ER, as described by Wallace and Populus (2022) and Daniela and Lytras (2018), exists. This study provides data that clearly defines where the inequality in access to ER exists. Based on the study results, the inequality they described can be found between low and high-SES classes, where high school students in lower-SES classes have lower levels of access to educational robotics.

ER is an integrated STEM education approach with proven benefits, including bolstering STEM skills and interests. The inequality found by this study suggests that students across different socioeconomic statuses inequitably gain these benefits. Students in higher SES regions have higher access to ER, which allows more students in those regions to participate in ER programs. Therefore, more students in those regions can reap the benefits of ER, such as improved computational thinking skills (Francisco José García-Peñalvo et al., 2020) and STEM skills (Ziaeeefard et al., 2020; Kim et al., 2015).

Furthermore, ER robotics has been shown to improve attitudes towards and increase interest in STEM fields and careers (Khanlari et al., 2013). Daniela and Lytras (2018) touted it as a method through which STEM education could be provided inclusively. This means that if students from backgrounds that make up the minorities in the STEM field have access to ER, the overall lack of diversity in the STEM field can be reduced. Yet, this study's results show that students from backgrounds that make up the minority population in the STEM field do not have access to ER. Both Black and Hispanic Americans are underrepresented in the STEM field, with Black Americans comprising 9% and Hispanic Americans comprising 15% of the STEM workforce (US National Science Foundation, 2023). Table 9 shows the average percentage of Black and Hispanic individuals in the sample taken for this study.

Table 9. Average Percent of Minorities in Sample

SES Group	Percent of Black Americans	Percent of Hispanic Americans
A	30.26%	25.96%
B	16.32%	23.21%
CD	14.43%	18%
DE	4.73%	13.72%
FG	5.30%	15.33%
GH	3.08%	9.19%

I	2.75%	7.19%
J	1.66%	6.18%

Note: The data in this table is from the American Community Survey (2022) by the US Census Bureau.

Table 9 shows a greater percentage of minority students in the lower SES regions. The data collected in this study suggests that ER is less available to students in lower SES regions, where more minority students are present. Therefore, ER is inherently less available to minority students. This could potentially contribute to the lack of diversity in the STEM field. With ER being such a valuable tool to improve the landscape of diversity in the STEM field, the innate inequality in access to ER will only hurt efforts to make the STEM field more diverse and inclusive.

Limitations

This study's sample was designed to represent NJ with a 90% confidence interval and a $\pm 6\%$ margin of error. The study sampled 120 regions across eight SES groups, yet the number of regions in each group was not split up evenly. Instead, the number of regions per SES group was split up to reflect the exact percentage breakdown of NJ (as shown in Table 2). This led to some SES groups having many regions in their sample (ex. "CD Regions" - 17 Regions samples) and others having very few regions in their sample (ex. "J Regions" - 5 Regions). The percentages of access to ER may have been exaggerated in the groups with few regions in their samples, specifically the A and J SES groups, since they only had 6 and 5 regions, respectively. Even though the overall sample size was large enough to generalize the findings to NJ, the sample size per SES group was too small. This led to the finding that in the J SES group, 100% of regions have access to ER, which is highly unlikely to be accurate. This could potentially mean that the correlation found in this study is not generalizable, as the percentages used to form it are exaggerated.

In this study, access to ER is defined as the presence of one or more robotics programs, free or paid, in a specific region. However, the term access to education is not necessarily limited to just the presence of education in a specific region; instead, it could be more extensive, considering the presence of education, participation, and student achievement (United Nations Education, Scientific, and Cultural Organization & Global Education Monitoring Report, 2020). This study fails to take those factors into account. Students may be unable to participate in an ER program in their region due to time constraints, financial commitments, or admission barriers. Therefore, despite the program being present in their region, it may not be accessible.

The study attempted to address this limitation by recording the average number of ER programs available to students (with access to at least one ER program) within each region, as shown in Table 8. Regions with more options for access to ER programs would likely have higher levels of participation due to fewer barriers. Table 8 clearly demonstrates an increase in the number of options available to a student as SES increases. Therefore, students in higher SES regions may have more accessible ER programs due to the increased presence and number of options in their regions. Nevertheless, since the study is a naturalistic observation and involves no human participants, it has no method of genuinely measuring the accessibility of ER in SES regions under the more extensive definition of access to ER. Therefore, the conclusion that access to ER increases with SES may be limited, as the more nuanced factors that determine access to the programs are unaccounted for.

Future Directions

It is important to note that SES is not necessarily the cause of the inequality in access to ER. The results of this study suggest that inequality exists between SES classes but does not identify the cause(s) of this inequality. Therefore, future researchers can investigate the different SES classes to determine the causes of this inequality. Ideally, this future research can allow policymakers, educational institutions, and the public to reduce this inequality and provide ER to all groups.

The findings of this study can also be used to provide solutions to this inequality. Wallace and Populus (2022) recommend developing innovation hubs in communities to promote equal access to ER. The findings of this study provide a more detailed location of where this solution could potentially be implemented: in low SES regions in NJ. Wallace and Populus' method is designed for communities in Greece with little access to ER. Future research could adapt this method or develop a new one based on the findings of this study, allowing for a more appropriate, precise solution to the inequality in ER.

Implications

Inequality in educational opportunities, like the one described in this study, can deter students from gaining upward social mobility (Brown, 2013). The results of this study demonstrate that students in lower SES classes may not have the same ER opportunities as students in higher SES classes; therefore, it could potentially deter them from social mobility, especially if they are disinterested in jobs in the STEM field.

Several educational nonprofit organizations operating in New Jersey and nationwide are working to counter STEM inequality and ER access. These nonprofits spend millions of dollars and hundreds of volunteer hours to improve equity in access to ER. One notable example is FIRST, the largest ER nonprofit operating globally. In 2023, FIRST spent over 11.2 million dollars on ER grants, allowing students to have the funds to participate in their programs (FIRST, 2023). The findings of this study identify that lower SES regions have lower levels of access to ER. Therefore, the findings provide educational nonprofit organizations, such as FIRST, with knowledge of the specific areas that need more aid or funding. This knowledge will allow these educational nonprofits to more effectively provide funds and manpower to help close the ER access gap.

Similarly, this study's findings could be valuable to public policy. As more emphasis shifts towards STEM, it is integral that public policy and educational curriculums continue to emphasize STEM education. Due to the benefits it provides in a single subject, ER is an excellent tool for this. Yet, to provide ER equitably, public policy must support regions that cannot access ER. The findings of this study provide policymakers with the knowledge that lower SES regions need the most support, therefore allowing for more effective support.

Conclusion

In conclusion, addressing the inequality in access to ER is crucial for promoting diversity, equity, and inclusion in STEM education and workforce development. The study identifies a significant inequality in access to ER for high school students between low and high-SES regions. This study was designed to be generalizable to all of the US, and its findings can play a positive role in reducing inequality in the ER and STEM fields.

Acknowledgments

I would like to thank my advisor for the valuable insight provided to me on this topic.

References

- Angel-Fernandez, J. M., & Vincze, M. (2018). Towards a Formal Definition of Educational Robotics. *Proceedings of the Austrian Robotics Workshop 2018*. <https://doi.org/10.15203/3187-22-1-08>
- Bhalla, A. S. (1992). *Uneven Development in the third world* (pp. 208–241). Springer.
- Broer, M., Bai, Y., & Fonseca, F. (2019). Socioeconomic inequality and educational outcomes. *IEA Research for Education*. <https://doi.org/10.1007/978-3-030-11991-1>
- Brown, P. (2013). Education, opportunity and the prospects for social mobility. *British Journal of Sociology of Education*, 34(5/6), 678–700. <https://doi.org/10.1080/01425692.2013.816036>
- Chachashvili-Bolotin, S., Milner-Bolotin, M., & Lissitsa, S. (2016). Examination of factors predicting secondary students' interest in tertiary STEM education. *International Journal of Science Education*, 38(3), 366–390. <https://doi.org/10.1080/09500693.2016.1143137>
- Daniela, L., & Lytras, M. D. (2018). Educational robotics for inclusive education. *Technology, Knowledge and Learning*, 24(2), 219–225. <https://doi.org/10.1007/s10758-018-9397-5>
- Dotson, V. M., Kitner-Triolo, M. H., Evans, M. K., & Zonderman, A. B. (2009). Effects of race and socioeconomic status on the relative influence of education and literacy on cognitive functioning. *Journal of the International Neuropsychological Society: JINS*, 15(4), 580–589. <https://doi.org/10.1017/S1355617709090821>
- Education Law Center. (2017). *ELC's updated district factor groups*. Education Law Center. <https://edlawcenter.org/research/elcs-updated-district-factor-groups/>
- Evripidou, S., Georgiou, K., Doitsidis, L., Amanatiadis, A. A., Zinonos, Z., & Chatzichristofis, S. A. (2020). Educational robotics: platforms, competitions and expected learning outcomes. *IEEE Access*, 8, 219534–219562. <https://doi.org/10.1109/access.2020.3042555>
- FIRST. (2023). *Annual report & Financials*. FIRST. <https://www.firstinspires.org/about/annual-report FIRST>. (2024, April 28). *Team and Event Search*. FIRST. <https://www.firstinspires.org/team-event-search#type=teams&sort=name&programs=FLLJR>
- Francisco José García-Peñalvo, Conde, M. Á., José Gonçalves, & Lima, J. (2020). Advances in computational thinking and robotics in education. *TEEM'20: Eighth International Conference on Technological Ecosystems for Enhancing Multiculturality*. <https://doi.org/10.1145/3434780.3436703>
- Hall, C., Dickerson, J., Batts, D., Kauffmann, P., & Bosse, M. (2011). Are we missing opportunities to encourage interest in STEM fields? *Journal of Technology Education*, 23(1). <https://doi.org/10.21061/jte.v23i1.a.4>
- Hendricks, C. C., Meltem Alemdar, & Ogletree, T. (2020). The impact of participation in VEX Robotics Competition on middle and high school students' interest in pursuing STEM studies and STEM-related careers. *2012 ASEE Annual Conference & Exposition*. <https://doi.org/10.18260/1-2--22069>
- Kennedy, C. M. (2015). Lessons from outside the classroom: What can New Zealand learn from the long Chilean winter? *Asia Pacific View Point*, 56(1), 169–181. <https://doi.org/10.1111/apv.12056>
- Khanlari, A. (2013). Effects of educational robots on learning STEM and on students' attitude toward STEM. *2013 IEEE 5th Conference on Engineering Education (ICEED)*. <https://doi.org/10.1109/iceed.2013.6908304>
- Kim, C., Kim, D., Yuan, J., Hill, R. B., Doshi, P., & Thai, C. N. (2015). Robotics to promote elementary education pre-service teachers' STEM engagement, learning, and teaching. *Computers & Education*, 91, 14–31. <https://doi.org/10.1016/j.compedu.2015.08.005>
- Kliucharev, G. A., & Kofanova, E. N. (2005). On the dynamics of the educational behavior of well-off and low-income Russians. *Russian Education and Society*, 47(11), 22–36. <https://doi.org/10.1080/10609393.2005.11056929>
- Martín Páez, et al. (2019). What are we talking about when we talk about STEM education? A review of literature.

- Science Education*. 103. 10.1002/sce.21522. <https://doi.org/10.1002/sce.21522>
- Martín-Páez, T., Aguilera, D., Perales-Palacios, F. J., & Vílchez-González, J. M. (2019). What are we talking about when we talk about STEM education? A review of literature. *Science Education*, 103(4), 799–822. <https://doi.org/10.1002/sce.21522>
- National Center for Education Statistics. (2013). *Improving the measurement of socioeconomic status for the National Assessment of Educational Progress*. https://nces.ed.gov/nationsreportcard/pdf/researchcenter/Socioeconomic_Factors.pdf
- Negrini, L., & Giang, C. (2019). How do pupils perceive educational robotics as a tool to improve their 21st century skills?. *Journal of E-Learning and Knowledge Society*, 15(2). <https://doi.org/10.20368/1971-8829/1628>
- New Jersey Department of Education. (1990). *District Factor Groups (DFG) for school districts*. www.nj.gov. <https://www.nj.gov/education/finance/rda/dfg.shtml>
- Oakes, M. (2006). *Measuring socioeconomic status*. <https://obssr.od.nih.gov/sites/obssr/files/Measuring-Socioeconomic-Status.pdf>
- Peter Ngugi Mwangi, Christopher Maina Muriithi, & Peace Byrne Agufana. (2022). Exploring the benefits of educational robots in STEM learning: A systematic review. *International Journal of Engineering and Advanced Technology*, 11(6), 5–11. <https://doi.org/10.35940/ijeat.f3646.0811622>
- Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia & Analgesia*, 126(5), 1763–1768. <https://doi.org/10.1213/ane.0000000000002864>
- Simon, M. K., & Goes, J. (2011). *Correlational research* [Unpublished Manuscript]
- State of New Jersey. (January 14th, 2022). School district boundaries [Interactive Map]. Retrieved from <https://njogis-newjersey.opendata.arcgis.com/datasets/newjersey::school-districts-unified-for-new-jersey/ab out>
- Tsui, L. (2007). Effective strategies to increase diversity in STEM fields: A review of the research literature. *The Journal of Negro Education*, 76(4), 555–581. <http://www.jstor.org/stable/40037228>
- United Nations Education, Scientific, and Cultural Organization, & Global Education Monitoring Report. (2020). *Defining the scope of inclusive education* (pp. 2–67).
- U.S. Census Bureau. (2022). *2018-2022 American Community Survey 5-year Public Use* [Data Set]. data.census.gov
- US National Science Foundation. (2023, January 30). *Diversity and STEM: Women, minorities, and persons with disabilities 2023*. NSF - National Science Foundation. nces.nsf.gov. <https://nces.nsf.gov/pubs/nsf23315/report>
- Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The Review of Higher Education*, 27(1), 45–73. <https://doi.org/10.1353/rhe.2003.0044>
- Wallace, M., & Pouloupoulos, V. (2022). Pursuing social justice in educational robotics. *Education Sciences*, 12(8), 565. <https://doi.org/10.3390/educsci12080565>
- Widya, Rifandi, R., & Laila Rahmi, Y. (2019). STEM education to fulfil the 21st century demand: a literature review. *Journal of Physics: Conference Series*, 1317(1317), 012208. <https://doi.org/10.1088/1742-6596/1317/1/012208>
- Ziaeeafard, S., Miller, M. H., Rastgaar, M., & Mahmoudian, N. (2017). Co-robotics hands-on activities: A gateway to engineering design and STEM learning. *Robotics and Autonomous Systems*, 97, 40–50. <https://doi.org/10.1016/j.robot.2017.07.013>