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A Data-Driven Analysis of Gender-Based Participation Barriers in Computer Science Education in Nigeria

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Abstract: Gender disparity in computer science education remains a major concern in developing countries, where socio-cultural expectations, economic constraints, institutional limitations, and psychological barriers influence students' educational choices. This study examines gender-based participation barriers in computer science education in Nigeria using a quantitative cross-sectional design. Data were collected from 520 respondents across secondary and tertiary institutions and analysed using descriptive statistics, reliability analysis, logistic regression, and ordinary least squares (OLS) regression. The findings reveal a significant gender gap, with male participation at 79.0% compared to 50.8% among female students. Logistic regression results show that female students have approximately 72% lower odds of participation than male students. Socio-cultural and economic barriers negatively affect participation, while institutional support and exposure to computing have positive effects. The OLS results indicate that socio-cultural barriers and female gender reduce interest in computer science, whereas exposure and institutional support significantly improve interest.The study concludes that gender disparity in computer science education is multidimensional and requires targeted interventions, including early exposure, mentorship, improved digital access, and gender-sensitive policies.

Keywords: Computer science education, gender disparity, participation barriers, digital inclusion, STEM.

1. Introduction

The expansion of digital technologies has made computer science education essential for economic development, innovation, and employability. However, gender disparity remains a persistent challenge, particularly in computing and engineering fields where women are underrepresented. The World Economic Forum (2023) emphasises that technology-related skills are becoming increasingly important for future employment, making equitable access to computer science education a key priority for developing economies. Despite the growing importance of computer science, gender disparity remains a major challenge in science, technology, engineering, and mathematics education. Globally, girls and women remain underrepresented in several STEM fields, particularly in computing and engineering, where participation is influenced by social norms, stereotypes, learning environments, self-confidence, and access to educational opportunities (UNESCO, 2017). Cheryan et al. (2017) argue that computer science is often perceived as a masculine field, and such perceptions can discourage girls from developing interest and confidence in computing-related disciplines.

In Nigeria, female students face multiple barriers including socio-cultural stereotypes, limited encouragement, inadequate access to resources, and low confidence in technical abilities. These barriers reduce participation, interest, and persistence in computer science education. The factors influencing female participation in computer science education are multidimensional. Socio-cultural expectations may discourage girls from pursuing computing by presenting it as a male-dominated field. Economic constraints, including limited access to computers, internet connectivity, and digital learning materials, can further restrict participation, especially among students from low-income and rural backgrounds (Hilbert, 2011). Institutional barriers, such as inadequate computer laboratories, limited mentorship, and lack of female role models, may also weaken female students' engagement. Dasgupta and Stout (2014) note that role models, supportive peers, and inclusive learning environments can improve girls' and women's persistence in STEM fields. Psychological factors are also important in explaining gender gaps in computer science education. Female students may experience lower self-efficacy, reduced confidence, and stereotype threat, especially when they are aware of negative assumptions about women's ability in technical disciplines. Steele (1997) explains that stereotype threat can affect academic identity, motivation, and performance among members of underrepresented groups. In computer science, this may reduce female students' willingness to participate or persist, even when they have the ability to succeed. Although previous studies have examined gender disparities in STEM education, there is still limited context-specific quantitative evidence on the barriers affecting female participation in computer science education in Nigeria. Much of the existing literature focuses on STEM broadly rather than computer science specifically.

This study adopts a data-driven approach to examine how socio-cultural, economic, institutional, psychological, and exposure-related factors influence gender-based participation in computer science education in Nigeria. By providing empirical evidence from the Nigerian context, the study contributes to research on gender equity, digital inclusion, and STEM education reform.

2. Literature Review

2.1 Gender Disparities in STEM and Computer Science Education

Gender disparity in STEM education remains a persistent global issue, particularly in computer science, engineering, physics, and other technical disciplines where female participation remains comparatively low. UNESCO (2017) notes that girls' and women's participation in STEM is shaped by family expectations, classroom climate, curriculum exposure, social norms, teacher attitudes, self-efficacy, and access to learning resources. OECD (2023) similarly observes that gender gaps are reflected not only in achievement but also in subject choices, confidence, career expectations, and advanced skill development. Computer science is among the STEM fields with the most persistent gender gaps. Cheryan et al. (2017) argue that women's underrepresentation in computer science is linked to masculine field cultures, limited early exposure, and stereotypes about who naturally belongs in computing. Master et al. (2016) also found that such stereotypes reduce girls' interest and sense of belonging. Earlier evidence by Margolis and Fisher (2002) shows that unequal early computing experience, male-dominated peer cultures, and narrow definitions of computing identity contribute to women's lower participation, while Blickenstaff (2005) argues that women are often filtered out of STEM through institutional practices, stereotypes, and weak support systems. In Nigeria, these issues are important because computer science education is central to digital transformation, youth employment, and national development. The current study therefore examines how socio-cultural, economic, institutional, psychological, and exposure-related barriers shape female participation in Nigerian computer science education.

2.2 Socio-Cultural Barriers and Gender Stereotypes

Socio-cultural norms strongly influence students' educational choices. Computing is often framed as technical, masculine, and more suitable for boys, which may affect parental encouragement, teacher expectations, peer attitudes, and students' career aspirations. Eccles (1994) explains that educational and occupational choices are shaped by expectations of success, subjective task value, socialization experiences, and gender-role beliefs. Cheryan et al. (2017) show that masculine stereotypes are stronger in computer science and engineering than in some other STEM fields, helping to explain their wider gender gaps. Master et al. (2016) further demonstrate that stereotypes can undermine girls' interest and sense of belonging in computer science learning environments. Ceci et al. (2009) argue that women's underrepresentation in science is strongly shaped by sociocultural context, while Wang and Degol (2017) identify ability beliefs, motivation, family expectations, values, and institutional opportunities as important influences on STEM gender gaps. In Nigeria, socio-cultural expectations may discourage girls from pursuing disciplines viewed as male-dominated or technically demanding. Families and communities may encourage female students toward fields considered more socially acceptable, while boys may receive stronger encouragement to explore technology and computing. This makes socio-cultural barriers central to understanding female participation in computer science.

2.3 Economic Barriers and the Digital Gender Divide

Economic inequality affects participation in computer science because the field requires access to digital devices, software, internet connectivity, electricity, and practical learning opportunities. Hilbert (2011) argues that the digital gender divide is closely linked to broader social and economic inequalities, especially in developing countries where access to information and communication technologies is uneven. Although economic barriers can affect all students, they may have stronger effects on girls when household resources are distributed unequally or when boys are prioritized for technology-related investment. Google and Gallup (2016) found that access to computer science learning opportunities is uneven and that underrepresented groups often face limited encouragement, fewer learning resources, and weaker exposure to computing. In Nigeria, economic barriers may be intensified by differences between urban and rural areas, public and private institutions, and income groups. Students in better-funded urban institutions may have greater access to laboratories, internet facilities, and qualified instructors, while students in rural or under-resourced schools may have limited exposure to computing. However, economic constraints alone do not fully explain gender disparity, as socio-cultural and psychological factors also strongly influence participation.

2.4 Institutional Barriers and Learning Environments

Institutional environments shape students' access to computer science through laboratories, qualified teachers, updated curricula, mentorship, inclusive teaching practices, and supportive policies. When these resources are absent, computer science may appear difficult, inaccessible, or unwelcoming. Blickenstaff (2005) argues that STEM institutions can reproduce gender exclusion through teaching practices, curricular assumptions, and organizational cultures. Dasgupta and Stout (2014) emphasize that female students' persistence in STEM improves when they encounter supportive peers, female role models, and inclusive institutional climates. Stout et al. (2011) similarly found that exposure to successful female experts can strengthen women's STEM self-concept and reduce the effects of stereotypes. The National Academies of Sciences, Engineering, and Medicine (2020) also stress that addressing women's underrepresentation requires institutional reforms, mentoring, inclusive policies, accountability, and sustained leadership commitment. For Nigerian computer science education, institutional barriers may include inadequate computing facilities, limited internet-enabled laboratories, shortages of trained teachers, few female mentors, and weak gender-sensitive policies. Institutional support is therefore necessary, although it must be combined with efforts to challenge stereotypes, expand access, and strengthen female students' confidence.

2.5 Psychological Barriers, Self-Efficacy, and Belonging

Psychological factors such as confidence, self-efficacy, motivation, interest, and sense of belonging are central to female participation in computer science. Steele's (1997) theory of stereotype threat explains that awareness of negative stereotypes can affect academic identity, performance, and persistence among underrepresented groups. In computer science, female students may experience this threat when they believe men are perceived as naturally more competent in technical fields. Master et al. (2016) found that stereotypes reduce girls' sense of belonging in computer science, while Sax et al. (2015) show that mathematical self-concept influences STEM aspirations. Hill et al. (2010) also argue that girls' and women's STEM participation can be improved by addressing implicit bias, stereotype threat, self-assessment patterns, spatial skills, and learning environments. These findings suggest that psychological barriers are not merely individual weaknesses but are shaped by social and institutional messages.

2.6 Reliability

All constructs recorded Cronbach's alpha values above 0.70, indicating acceptable internal consistency.

2.7 Ethical Considerations

Ethical approval was obtained from the relevant academic body, and informed consent was obtained from all participants.

3. Methodology

3.1 Research Design

A quantitative cross-sectional design was adopted to examine participation barriers at a single point in time.The design was suitable because the study measured the relationship between gender, perceived barriers, institutional support, exposure to computing, and participation outcomes at a specific point in time. It also allowed for comparison across gender, educational level, institution type, and geographic location.

3.2 Study Population and Sampling

The study focused on students in secondary and tertiary educational institutions in Nigeria. The target population included secondary school students, undergraduates, and postgraduates who were either enrolled in computer science-related programmes or positioned to make educational choices related to computer science. A stratified sampling technique was used to ensure representation across gender, educational level, institution type, and geographic location.

The minimum sample size was calculated using Cochran's formula:

$$n = \frac{Z^2 p(1-p)}{e^2}$$

where n_0 is the minimum sample size, Z is the standard normal value at 95% confidence level, p is the estimated population proportion (0.5), and e is the margin of error. Using $Z = 1.96$, $p = 0.50$, and $e = 0.05$. The minimum sample size was 384; however, 520 responses were used to improve reliability.

3.3 Data Collection Instrument

Data were collected using structured questionnaires administered across selected secondary and tertiary institutions in Nigeria. The questionnaire covered demographic characteristics, participation status, socio-cultural barriers, economic constraints, institutional support, psychological factors, and exposure to computing. Most items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire was reviewed for clarity, relevance, and alignment with the study objectives before administration.

3.4 Measurement of Variables

The dependent variable was participation in computer science education. Participation was coded as 1 for respondents enrolled in computer science or related computing programmes and 0 for those not enrolled. A composite interest and engagement score was also developed to measure motivation and engagement with computer science. The independent variables were grouped into five constructs: socio-cultural barriers, economic barriers, institutional support, psychological factors, and exposure to computing. Socio-cultural barriers included stereotypes, parental expectations, cultural norms, and peer influence. Economic barriers included access to computers, internet connectivity, affordability of digital resources, and electricity. Institutional support covered computer laboratories,

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teacher support, mentorship, and gender-sensitive policies. Psychological factors included confidence, self-efficacy, fear of failure, and sense of belonging, while exposure to computing included early computer access, prior computing experience, coding activities, and encouragement from teachers, parents, or peers.

3.5 Validity and Reliability

Content validity was established by ensuring that the questionnaire items reflected the major constructs identified in the literature. Construct validity was assessed using exploratory factor analysis, supported by the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Reliability was assessed using Cronbach's alpha. A threshold of 0.70 was adopted as the minimum acceptable level of internal consistency. Constructs with alpha values above this threshold were considered reliable for further analysis.

3.6 Model Specification

Logistic regression was used to examine the determinants of participation in computer science education because the dependent variable was binary. The model was specified as:

$$\mathrm{logit}(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 GEN_i + \beta_2 SCB_i + \beta_3 ECB_i + \beta_4 INS_i + \beta_5 PSY_i + \beta_6 EXP_i + \epsilon_i$$

where P_i is the probability of participation, GEN_i represents gender, SCB_i socio-cultural barriers, ECB_i economic barriers, INS_i institutional support, PSY_ipsychological factors, EXP_iexposure to computing, and $\epsilon_i$the error term.

Ordinary least squares regression was also used to examine determinants of interest and engagement in computer science:

$$INT_i = \beta_0 + \beta_1 GEN_i + \beta_2 SCB_i + \beta_3 ECB_i + \beta_4 INS_i + \beta_5 PSY_i + \beta_6 EXP_i + \epsilon_i$$

where INT_i represents the composite interest and engagement score.

3.7 Data Analysis Procedure

Data were screened for missing values, inconsistent responses, and outliers before analysis. Descriptive statistics were used to summarise respondent characteristics and participation patterns. Cross-tabulations were used to compare participation by gender, location, and institution type. Pearson correlation analysis was used to examine relationships among variables. Logistic regression was used to estimate participation likelihood, while OLS regression was used to examine predictors of interest and engagement. Model performance was assessed using pseudo-R^2, classification accuracy, area under the ROC curve, adjusted R^2, coefficient estimates, and p-values. Robustness checks were conducted using variance inflation factor, heteroskedasticity assessment, and residual diagnostics to ensure the reliability of the estimates.

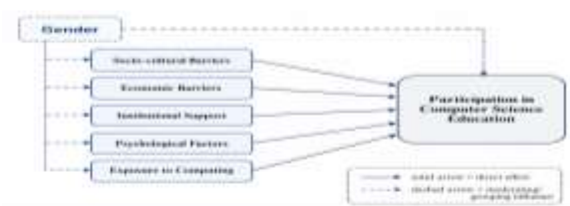
3.8 Ethical Considerations

The study followed standard ethical principles for research involving human participants. Respondents were informed about the purpose of the study, participation was voluntary, and confidentiality was maintained. No personally identifiable information was reported, and data were analysed in aggregate form for academic purposes only.

3.9 Conceptual Framework of the Study

The conceptual structure of the study is presented in Figure 1. The framework shows that participation in computer science education is influenced by five major explanatory dimensions: socio-cultural barriers, economic barriers, institutional support, psychological factors, and exposure to computing. Gender is treated as a grouping and moderating variable because male and female students may experience these barriers differently.

Figure 1. Conceptual framework showing the relationship between gender-based barriers and participation in computer science education.



The framework provides the basis for the empirical analysis. It assumes that socio-cultural, economic, and psychological barriers are likely to reduce participation, while institutional support and exposure to computing are expected to increase participation. Gender may influence the strength and direction of these relationships because female students often experience stereotypes, limited encouragement, and lower confidence more strongly than male students.

4. Results and Discussion

This section presents the empirical results on gender-based participation barriers in computer science education in Nigeria. The analysis covers respondent characteristics, participation patterns, reliability of measurement

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constructs, gender-based differences in perceived barriers, regression results, and the implications of the findings. The tables and figures included in this section are based on the study dataset of 520 respondents and the reported statistical outputs.

4.1 Demographic and Institutional Characteristics of Respondents

A total of 520 valid responses were analysed. As shown in Table 1, male respondents accounted for 52.3% of the sample, while female respondents represented 47.7%. This distribution provides a balanced basis for gender-based comparison. Most respondents were undergraduate students, representing 65.4% of the sample, followed by secondary school students at 24.6% and postgraduate students at 10.0%. Public institutions accounted for 71.5% of respondents, while private institutions represented 28.5%. In terms of geographic location, 46.9% of respondents were from urban areas, 30.4% from semi-urban areas, and 22.7% from rural areas.

Table 1. Demographic and institutional profile of respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	272	52.3
	Female	248	47.7
Education level	Secondary school	128	24.6
	Undergraduate	340	65.4
	Postgraduate	52	10.0
Institution type	Public	372	71.5
	Private	148	28.5
Location	Urban	244	46.9
	Semi-urban	158	30.4
	Rural	118	22.7
Total		**520**	**100.0**

The demographic composition indicates that the sample was sufficiently distributed across major categories relevant to the study. The inclusion of respondents from different educational levels, institution types, and geographic locations strengthens the comparative value of the analysis.

4.2 Participation by Gender

The overall participation rate was 65.6%. However, Table 2 and Figure 2 show a substantial gender gap. Male respondents had a participation rate of 79.0%, while female respondents had a participation rate of 50.8%. This represents a gender participation gap of 28.2 percentage points.

Table 2. Participation by gender

Gender	Total Respondents	Participation Rate (%)	Estimated Participants	Estimated Non-Participants
Male	272	79.0	215	57
Female	248	50.8	126	122
Total	**520**	**65.6**	**341**	**179**

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Figure 2. Participation rate in computer science education by gender.

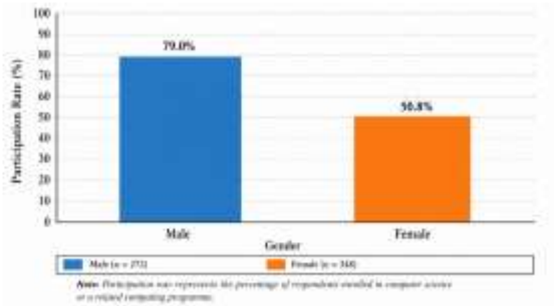

Figure 2 visually confirms the gender disparity in participation. The participation rate among male respondents was substantially higher than that of female respondents, suggesting that female students remain underrepresented in computer science education. This finding supports the argument that gender disparity in computer science is not merely a matter of individual preference but may reflect deeper socio-cultural, psychological, and institutional constraints. The difference between male and female participation also indicates that female students may face barriers that discourage enrolment or active engagement in computer science. These barriers may include stereotypes about computing, limited family or peer encouragement, lack of female role models, and lower confidence in technical ability.

4.4 Participation in Computer Science Education by Geographic Location

Participation rates also differed across geographic locations. As shown in Table 3, urban respondents had the highest participation rate at 71.3%, followed by semi-urban respondents at 64.6%. Rural respondents recorded the lowest participation rate at 55.1%.

Table 3. Participation in computer science education by geographic location

Location	Total Respondents	Participation Rate (%)	Estimated Participants	Estimated Non-Participants
Urban	244	71.3	174	70
Semi-urban	158	64.6	102	56
Rural	118	55.1	65	53
Total	**520**	**65.6**	**341**	**179**

The results indicate a clear location-based participation pattern. Urban respondents were more likely to participate in computer science education than rural respondents. The difference between urban and rural participation was 16.2 percentage points. This suggests that geographic inequality may affect access to computer science education through differences in school infrastructure, internet connectivity, availability of computer laboratories, teacher quality, and exposure to digital learning opportunities. The lower participation rate among rural respondents is particularly important for policy because it suggests that gender-based interventions should also consider location-based disadvantage. Female students in rural areas may experience compounded barriers due to both gender norms and limited digital infrastructure.

4.5 Participation by Institution Type

Institution type also influenced participation patterns. Table 4 show that respondents from private institutions had a participation rate of 73.6%, compared with 62.4% among respondents from public institutions.

Table 4. Participation in computer science education by institution type

Institution Type	Total Respondents	Participation Rate (%)	Estimated Participants	Estimated Non-Participants
Public	372	62.4	232	140
Private	148	73.6	109	39
Total	**520**	**65.6**	**341**	**179**

The result indicates an institution-based participation gap of 11.2 percentage points. Respondents from private institutions were more likely to participate in computer science education than those from public institutions. This may reflect better access to digital infrastructure, smaller class sizes, more reliable computer laboratories, better internet connectivity, and stronger institutional support in some private institutions. However, because public institutions represent the majority of the sample, improving computer science participation in public institutions is critical for broadening access. Investments in computer laboratories, teacher training, digital resources, and gender-sensitive academic support could help reduce this institutional gap.

4.6 Comparison of Major Participation Gaps

Table 5 and Figure 3 compare the three major participation gaps identified in the study: gender, location, and institution type. The largest gap was observed by gender, followed by location and institution type.

Table 5. Summary of major participation gaps

Comparison Group	Higher Participation Group	Lower Participation Group	Participation Gap
Gender	Male: 79.0%	Female: 50.8%	28.2 percentage points
Location	Urban: 71.3%	Rural: 55.1%	16.2 percentage points
Institution type	Private: 73.6%	Public: 62.4%	11.2 percentage points

Figure 3. Comparison of major participation gaps in computer science education.

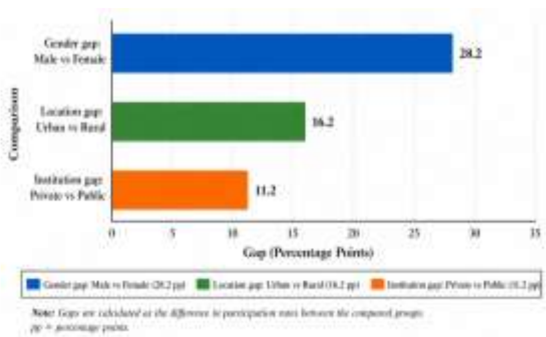

Figure 3 shows that the gender gap was the most pronounced disparity in the dataset. The 28.2 percentage-point difference between male and female respondents was larger than the urban-rural gap and the private-public institution gap. This finding confirms that gender is a central dimension of inequality in computer science education. The result also shows that location and institution type remain important. Participation was lower among rural respondents and respondents from public institutions. Therefore, gender inequality in computer science education should not be examined in isolation. Instead, it should be understood as intersecting with institutional and geographic inequalities.

4.7 Reliability and Construct Validation

Reliability analysis was conducted to determine the internal consistency of the measurement constructs. The study measured five major constructs: socio-cultural barriers, economic barriers, institutional support, psychological factors, and exposure/support. The manuscript reports that all constructs exceeded the acceptable reliability threshold of 0.70, indicating that the measurement scales were internally consistent.

Table 6. Measurement constructs and operational definitions

Construct	Operational Definition	Example Indicators	Expected Relationship with Participation
Socio-cultural barriers	Social and cultural conditions that discourage participation in computer science	Gender stereotypes, parental expectations, cultural norms, peer influence	Negative
Economic barriers	Financial and resource-related constraints affecting access to computing	Access to computers, internet access, affordability of digital tools, electricity	Negative

Institutional support	School or university-level support for computer science learning	Computer laboratories, teacher support, mentorship, institutional policies	Positive
Psychological factors	Individual-level confidence and perceived ability in computer science	Self-efficacy, confidence, fear of failure, sense of belonging	Positive when confidence is high; negative when psychological barriers are high
Exposure to computing	Prior access to computing experiences before or during formal education	Early computer access, coding exposure, digital literacy training	Positive
Participation	Enrolment or active engagement in computer science education	Enrolled=1; not enrolled = 0	Dependent variable

Table 7. Reliability and construct validation reporting format

Construct	Number of Items	Cronbach's Alpha	Reliability Decision
Socio-cultural barriers	Not reported	> 0.70	Acceptable
Economic barriers	Not reported	> 0.70	Acceptable
Institutional support	Not reported	> 0.70	Acceptable
Psychological factors	Not reported	> 0.70	Acceptable
Exposure/support	Not reported	> 0.70	Acceptable

The reliability results indicate that the questionnaire items were suitable for measuring the constructs used in the study. For final journal submission, the exact Cronbach's alpha values should be included for each construct. This will strengthen the transparency and replicability of the study.

4.8 Gender Differences in Participation Barriers

The comparative analysis showed that female respondents experienced higher socio-cultural and psychological barriers than male respondents. This suggests that female students were more likely to encounter gender stereotypes, cultural expectations, reduced encouragement, lower confidence, and weaker perceived belonging in computer science. Economic barriers did not show a strong gender difference, suggesting that financial constraints affected both male and female respondents. However, the stronger socio-cultural and psychological barriers reported by female respondents indicate that female underrepresentation cannot be explained by economic disadvantage alone. This finding is important because it shows that increasing access to computers and internet facilities may not be sufficient if gender norms and confidence-related barriers remain unaddressed. Female students may need targeted mentorship, exposure to female role models, supportive classroom environments, and interventions that challenge stereotypes about computing.

4.9 Logistic Regression Results: Determinants of Participation

Logistic regression was used to estimate the likelihood of participation. The model demonstrated acceptable predictive performance, as shown in Table 8 and Figure 8. The pseudo-R^2 value was 0.145, the area under the receiver operating characteristic curve was 0.747, and the classification accuracy was 0.723.

Table 8. Logistic regression model summary

Model Statistic	**Value**

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Dependent variable	Participation in computer science education
Model type	Binary logistic regression
Pseudo R^2	0.145
AUC	0.747
Classification accuracy	0.723
Female odds ratio	0.28
Interpretation of female odds ratio	Female respondents had approximately 72% lower odds of participation than male respondents

The AUC value of 0.747 indicates that the model had acceptable discriminatory ability in distinguishing participants from non-participants. The classification accuracy of 0.723 also suggests that the model correctly classified a reasonable proportion of cases. The odds ratio for female respondents was 0.28. This means that, after controlling for other factors, female respondents had substantially lower odds of participating in computer science education compared with male respondents. Specifically, the odds of participation among female students were approximately 72% lower than those of male students. The model further showed that socio-cultural and economic barriers negatively influenced participation, while institutional support and exposure/support had positive effects. Exposure/support emerged as a particularly important positive predictor, indicating that early exposure to computing and supportive learning environments can increase participation.

Table 9. Logistic regression direction of effects

Predictor	Direction of Effect on Participation	Statistical Interpretation
Female	Negative	Significant negative effect
Socio-cultural barriers	Negative	Significant negative effect
Economic barriers	Negative	Significant negative effect
Institutional support	Positive	Positive but marginally significant
Exposure/support	Positive	Strong positive effect

The logistic regression results confirm that participation in computer science education is shaped by multiple factors. Gender remains a strong predictor, but socio-cultural, economic, institutional, and exposure-related variables also influence participation outcomes.

4.10 OLS Regression Results:

Table 10: Determinants of Interest in Computer Science

Ordinary least squares regression was used to examine the factors influencing interest in computer science. The model produced an adjusted R^2 of 0.257, indicating moderate explanatory power. The results are presented in Table 10 and Figure 4.

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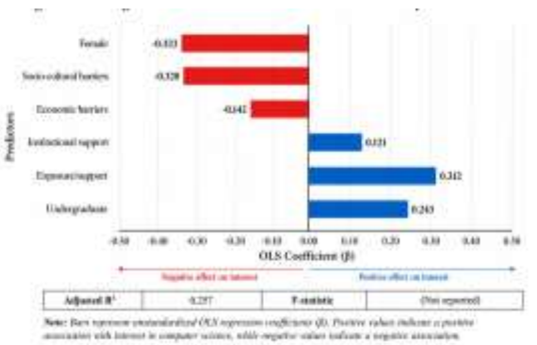
Table 10. OLS regression results for predictors of interest in computer science

Predictor	Coefficient (β)	p-value	Interpretation
Female	-0.323	0.046	Female respondents reported lower interest in computer science
Socio-cultural barriers	-0.320	< 0.001	Strong negative effect on interest
Economic barriers	-0.142	0.010	Negative effect on interest
Institutional support	0.121	0.032	Positive effect on interest
Exposure/support	0.312	< 0.001	Strong positive effect on interest
Undergraduate	0.243	0.027	Undergraduate status positively influenced interest
Adjusted R^2	0.257		Moderate explanatory power

Figure 4. OLS regression coefficients for predictors of interest in computer science education.



The OLS results show that female gender and socio-cultural barriers negatively predicted interest in computer science. The coefficient for female respondents was -0.323, indicating that female respondents had lower interest scores than male respondents, holding other variables constant. Socio-cultural barriers also had a strong negative coefficient of -0.320, showing that stereotypes, cultural expectations, and social discouragement reduce interest in computer science. Economic barriers also had a negative effect on interest, although the magnitude was smaller than that of socio-cultural barriers. This suggests that limited access to resources, affordability challenges, and poor digital infrastructure can reduce interest, but the strongest discouraging influence came from socio-cultural factors. Institutional support and exposure/support had positive effects on interest. Exposure/support had one of the strongest positive coefficients at 0.312, confirming that early access to computing, encouragement, and supportive learning experiences are important for developing interest in computer science. Institutional support also had a positive effect, suggesting that computer laboratories, teacher support, mentorship, and gender-sensitive policies can improve students' interest.

4.12 Discussion of Findings

The results provide strong evidence that gender-based participation barriers remain a significant issue in computer science education in Nigeria. The gender participation gap of 28.2 percentage points shows that female students are considerably less likely to participate in computer science education than male students. This finding is consistent with the broader argument that computing is often perceived as a male-dominated field, which can discourage female students from developing interest and confidence. The location-based findings show that rural respondents had lower participation than urban respondents. This suggests that geographic inequality remains an important factor in computer science education. Rural students may face limited access to computers, unreliable internet connectivity, inadequate school infrastructure, and fewer opportunities for early exposure to digital learning. Female students in rural areas may be especially disadvantaged when these structural barriers combine with socio-cultural expectations. The institution-based results also show that respondents from private institutions had higher participation than those from public institutions. This may reflect differences in facilities, teacher support, digital resources, and institutional investment. Since most respondents were from public institutions, improving computer science infrastructure and support in public schools and universities is essential for expanding equitable participation.

The findings show moderate but consistent evidence of gender disparity in computer science education. Female

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students face stronger socio-cultural and psychological barriers, which significantly reduce participation and interest. The strong positive effect of exposure/support is one of the most important findings of the study. It suggests that early computing exposure, coding activities, digital literacy programmes, encouragement from teachers and parents, and mentorship can increase both participation and interest. Therefore, interventions should begin before students reach tertiary education. Early exposure at primary and secondary levels may help reduce gender stereotypes and improve female students' confidence in computing.

The results also indicate that infrastructure alone is not enough. Although institutional support matters, socio-cultural and psychological barriers remain central. Female students may still avoid computer science if they perceive it as masculine, difficult, or socially unsuitable. Therefore, policies should combine digital access with mentorship, gender-sensitive teaching, role model visibility, and community-level awareness campaigns.

4.13 Policy and Practical Implications

The findings suggest several practical interventions for improving gender equity in computer science education. First, early exposure to computing should be expanded through coding clubs, digital literacy programmes, robotics activities, and school-based computer science curricula. Second, female mentorship programmes should be introduced to provide students with visible role models in computer science and related fields. Third, public institutions and rural schools require targeted investment in computer laboratories, internet connectivity, electricity, and teacher training.

Fourth, gender stereotypes should be addressed through awareness campaigns involving parents, teachers, students, and community stakeholders. Fifth, schools and universities should adopt gender-sensitive policies that support inclusive classroom practices, prevent discrimination, and encourage female participation in computing activities.

Table 12. Recommended policy intervention matrix

Identified Barrier	Empirical Evidence	Recommended Intervention	Expected Outcome
Gender stereotypes	Female students reported lower participation and higher socio-cultural barriers	Gender-sensitisation campaigns in schools and communities	Improved perception of computer science as gender-inclusive
Low female confidence	Female students experienced stronger psychological barriers	Mentorship and confidence-building programmes	Improved self-efficacy and persistence
Limited early exposure	Exposure/support strongly predicted participation and interest	Coding clubs, robotics clubs, early digital literacy programmes	Increased early interest in computing
Weak institutional support	Institutional support positively influenced interest	Improve computer laboratories, teacher training, and gender-sensitive policies	More inclusive learning environments
Rural disadvantage	Rural respondents had lower participation	Expand digital infrastructure and computer access in rural schools	Reduced geographic participation gap
Public institution disadvantage	Public institutions had lower participation than private institutions	Increase investment in ICT facilities in public schools	Improved institutional equity
Economic constraints	Economic barriers negatively affected participation and interest	Subsidised devices, internet access, and learning materials	Improved access for disadvantaged students

Conclusion

This study examined gender-based participation barriers in computer science education in Nigeria. The findings show that female students remain significantly underrepresented, with female participation at 50.8% compared with 79.0% among male respondents. This confirms a substantial gender participation gap in computer science education. The results further indicate that participation is shaped by socio-cultural, economic, institutional, psychological, and exposure-related factors. Socio-cultural barriers and economic constraints reduced participation and interest, while institutional support and exposure to computing improved students' engagement. The study also found that rural respondents and students from public institutions recorded lower participation rates, suggesting that gender inequality intersects with geographic and institutional disadvantage.

This study demonstrates that gender disparity in computer science education in Nigeria is influenced by multiple interacting factors. While infrastructure is important, addressing socio-cultural and psychological barriers is critical. Effective intervention should include early exposure to computing, mentorship programmes, female role models, gender-sensitive teaching practices, improved access to digital resources, and community-level efforts to challenge stereotypes that present computer science as a male-dominated field. Overall, the study contributes empirical evidence on gender-based participation barriers in Nigerian computer science education and provides a basis for policies aimed at promoting gender equity, digital inclusion, and a more diverse technology workforce.

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