Design and Evaluation of a Data Analytics Boot Camp for Nigerian High School Students

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ABSTRACT

The growing demand for data-driven decision-making across industries has intensified the need for data analytics education at all levels, including secondary schools. This study examines the design, implementation, and evaluation of a one-week data analytics summer boot camp specifically designed for senior secondary school students in Nigeria. The boot camp introduced students to foundational data tools such as Microsoft Excel and Python through hands-on, project-based learning, while also promoting self-discovery, career awareness, and Science Technology Engineering Mathematics (STEM) engagement. A total of 36 students participated in the camp, selected from 50 applications based on STEM background and motivation. The program featured interactive workshops, collaborative group projects, and university department tours. Instruction emphasized experiential learning. Pearson correlation analysis was used to explore relationships between prior exposure and post-boot camp engagement. Correlation results revealed only weak positive relationships between prior exposure and engagement ($r \approx 0.17–0.21$), suggesting that students with no prior exposure to data analytics tools/knowledge were equally capable of engaging meaningfully with the content. Subgroup analysis showed minimal differences in confidence and perceived challenge between male and female students, indicating a relatively inclusive learning environment. Further results showed that students demonstrated high levels of engagement and confidence, with an average Excel confidence rating of 4.09 and engagement score of 4.39 on a 5-point scale. The quantitative analysis was supported with qualitative analysis of the responses from mentors, instructors, and judges, with 5 key themes emerging. Overall, the findings from this research affirm the potential of boot camps as an effective and inclusive platform for fostering digital and data literacy among high school students, particularly in low-resource settings.

KEYWORDS

Data Analytics
Python Programming
Excel
Experiential Learning
Boot Camp Model
STEM
Technology Education
Digital Literacy

1. INTRODUCTION

The increase in demand for making data-driven decisions across various industries has created a need for professionals with data analytics skills (Stanton & Stanton, 2019; Johnson et al., 2021). Data analytics is a key component of business strategy that enables organizations to gain insights, optimize operations, and drive innovation (Stanton & Stanton, 2019; Johnson et. al., 2021). However, the demand for data analytics professionals far exceeds the current supply, resulting in a significant skills gap (Li et. al., 2021).

To address this gap, various educational institutions are beginning to incorporate data analytics into their curricula, starting from secondary school (Schanzer et al., 2021). Data analytics offers numerous benefits for students, making a strong case for its early integration into education. As a rapidly growing field, it equips learners with the foundational skills needed for rewarding and in-demand careers. Beyond career preparation, engaging with data analytics fosters critical thinking and problem-solving abilities, as students learn to work with complex datasets, identify patterns, and draw meaningful inferences. Furthermore, because data analytics is inherently interdisciplinary—drawing from mathematics, statistics, computer science, and domain-specific knowledge—it serves as an effective catalyst for sparking interest in STEM education and enhancing overall STEM learning experiences.

However, designing effective data analytics education programs for high school students, especially in Africa, poses significant challenges. A major hurdle is the limited availability of resources. Many secondary schools lack both the financial and technical resources necessary to foster data analytics education. In addition, there is inadequate teacher training. Many secondary school teachers in Africa do not have the technical skills to facilitate data science training or education. Finally, students have diverse educational experiences and varying levels of computer proficiency, making it challenging to design training that meets the needs of all.

In Africa, there is a growing interest in integrating computational thinking and data science into secondary school curricula as a strategy to bridge digital divides and support sustainable development (Mhlanga & Moloi, 2020). Informal learning environments such as mentorship programmes, boot camps, group discussion, project-based learning have been identified as a means that can motivate and sustain learners to pursue STEM-based courses (Isphording and Qendra, 2019; Roberts at. al., 2018; Kelley & Knowles, 2016; Yilmaz et. al., 2009). Boot camp style has been identified as a key approach that can be used to teach tech-based courses because it offers an intensive and hands-on learning experience (Tu et. Al., 2018). Boot camps can provide students with the opportunity to work on real-world projects, collaborate with peers, and receive feedback from instructors (Sakpere et. al., 2024). However, there is a limited number of data analytics boot camps available, particularly for high school students (Sousa et. al., 2021). This gap underscores the novelty and significance of the present study, which documents a locally contextualized intervention aimed at equipping Nigerian secondary school students with foundational data analytics skills. By situating this study within a region that is underrepresented in the literature, it offers valuable insights into the feasibility, challenges, and potential of implementing data analytics education in resource-constrained educational settings. Our research questions are as follows: What baseline gaps exist in digital and analytical skills among high school students in underserved communities? How does a student's confidence in using data analytics tools like Excel and Python change from participation in a data analytics boot camp?

In this research, we first attempted to understand the baseline gaps that exist in data analytics skills among a targeted high school students in an underserved community. Afterward, a Summer Boot Camp was designed to introduce them to data analytics using practical tools like Microsoft Excel and Python. Specifically, we design the curriculum to introduce them to skills in Excel that revolve around data visualization in a manner that they can create a dashboard, while for Python, it was designed to equip them with writing simple codes using variable declaration, math

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expressions and control structures. Beyond technical skills, the boot camp focused on fostering self-discovery, academic exploration, and career planning. This paper documents the boot camp's structure, content delivery, student feedback, and overall impact using standard educational research methods. The study situates the boot camp within ongoing global and regional conversations around STEM education and youth empowerment.

2. RELATED WORKS

Data analytics education in high school is evolving with a limited number of programs and courses available (Sousa et. al., 2021). However, various studies have recognized the importance of teaching data analytics in high schools (Schanzer et. al., 2021; Sami et. al., 2020; Weiland & Engledowl, 2022; Frischemeier et. al., 2021). According to Weiland and Engledowl (2022), there is a critical need for a change in K-12 education to build capacity for data science education. To achieve this, they call for collaborative efforts among educators, policymakers, and researchers to transform curricula and equip students with essential data literacy skills for active participation in a data-driven world. The research of Sami et. al.(2020) is focused on the potential of integrating data science with an agricultural context to engage high school students. Their emphasis was on the importance of hands-on, project-based learning and the use of real-world data to enhance student understanding and interest in data analytics and related careers.

To further drive data analytics education, especially in this technologically evolving world, boot and summer camps have emerged as a popular approach to teaching STEM-based courses offering an intensive, hands-on learning experience and creating inclusion (Martín-Peciña et. al., 2025; Dekhane et. al., 2016; Novick & Gadura, 2020). Boot camps serve as accelerated pathways for skill acquisition, particularly effective for coding, data science, and other high-demand technical domains. These boot camps typically provide a structured learning experience, mentorship, and project-based work, with a focus on developing practical skills (Sakpere et. al., 2024). Data analytics requires a unique combination of technical, business, and soft skills (Davenport, 2014). The key skills and knowledge required for data analytics include Programming languages such as Python, which has been identified as suitable for beginners (Sakpere, 2019); Data visualization tools such as Excel; Statistical concepts such as regression, and machine learning algorithms such as decision trees.

Although boot camps have been identified as an effective means of providing hands-on training, there is a lack of documented research on their implementation in the field of data science, particularly within resource-constrained environments such as Nigeria, and among high school and secondary school students. This research fills this gap by exploring how data analytics can be introduced through intensive and localized boot camps in underserved educational environments.

3. METHODOLOGY

This section describes the methodology used in the design, implementation, and evaluation of the five-day data analytics boot camp. The goal is to document the process clearly and in a way that allows others to replicate the program.

3.1 Recruitment and participation

A recruitment form was designed and shared widely with the senior students at a targeted high school in the South West of Nigeria with a background in STEM. Our choice of school is based on their interest in embracing technology. The recruitment form had over 20 fields that included demographics, prior knowledge, access to devices, motivation, and previous experiences. A total of 54 responses were received, and upon cleaning, 4 duplicated records were removed. A total of 40 students were shortlisted to participate. The shortlisting was done using the following criteria: students' interest, parents' permission, and prior computer literacy. Out of the 40 shortlisted students, a total of 36 students registered and participated in the boot camp. Four shortlisted participants couldn't join due to illness and last-minute plan changes. Students were organized into smaller working groups to encourage collaboration, peer learning, and project-based engagement.

3.2 Boot camp design

The boot camp style of learning was "learning by doing". It was a hands-on workshop and bootcamp, where mentors were available to help provide guidance. No more than 20-25% of the course was instructor-led lecturing. The remainder of the time was dedicated to hands-on activities, workshops, tutorials, groupwork, exercises, etc. The rationale for this is that we believe learners will grasp the material best by taking initiative, so we highly encourage students to ask questions, engage with their peers, and review relevant resources.

Two key pedagogies were utilized:

a. Project-based learning (PBL) is a way of teaching that lets students explore real-world problems and create solutions.

b. Collaborative Learning: Collaborative learning is the educational approach of using groups to enhance learning through working together. Groups of two or more learners work together to solve problems, complete tasks, or learn new concepts (Herrera-Pavo, 2021).

The Boot Camp lasted five consecutive days. Each day included structured activities such as lectures, interactive sessions, lab exercises, self-discovery workshops, and academic visits. The tools used were Microsoft Excel for data visualization and Python for basic programming. These tools were selected because they are fundamental and easy for beginners (Sakpere, 2019; Schwabish, 2023).

3.3 Program structure and delivery

The boot camp spanned five consecutive days, each featuring a combination of lectures, interactive sessions, departmental tours, and practical activities. The instructional design emphasized experiential learning and was delivered by professionals with expertise in data analytics, education, and career development. A summary of the activities of each day is given as follows:

a. Day 1 focused on foundational concepts in data analytics. Students were introduced to real-world applications of data analysis through keynote presentation and hands-on activities in Microsoft Excel. Topics included data collection, cleaning, and basic Excel functions. The day concluded with a departmental tour of the Mathematics and Computer Science departments of the University of Ibadan.

b. Day 2 began with a self-discovery and career orientation session, where students reflected on personality traits and future aspirations. This was followed by instruction in advanced Excel features such as pivot tables, conditional formatting, and data visualization. Students also rotated departmental tours to ensure exposure to both mathematical and computing academic tracks.

c. Day 3 involved a two-part session. In the morning, students developed Excel dashboards based on pre-cleaned datasets. The afternoon introduced Python programming fundamentals, led by a group of facilitators who presented core programming concepts including data types, expressions, and control structures. The day ended with a visit to the Department of Electrical Engineering, including a tour of a 3D fabrication laboratory.

d. Day 4 served as the project day, where students were evaluated through two practical tasks. The first task required students to clean and analyze a dataset using Excel and present their findings through a dashboard. The second task assessed Python comprehension through a basic programming exercise involving mathematical operations and structured code.

e. Day 5 was dedicated to project presentations and evaluation. A panel of three judges—university faculty with backgrounds/experience in computing and education/ environmental study —assessed the projects based on content accuracy, analytical depth, code logic, presentation clarity, and creativity. Recognition was given to the top-performing teams, and an additional award was presented to the most diligent student as determined by the mentors.

3.4 Assessment and evaluation

Learning outcomes were assessed through project-based evaluations and real-time participation. Additionally, a post-program feedback form was administered to participants to evaluate:

a. Perceived learning gains
b. Confidence using Excel and Python
c. Engagement with the instructional style and content
d. Challenges encountered during the boot camp

The feedback and project outcomes served as formative assessment, informing recommendations for future iterations of the program. This study positions its findings as a **first step toward developing inclusive data science education for high school learners**.

4. RESULTS

This section presents the analysis of both the pre-boot camp and post-boot camp data. It begins with a review of the applicants' details before the program, then evaluates their experiences after participating in the boot camp. It concludes with a comparative analysis of the pre- and post-boot camp findings.

4.1 Baseline characteristics of applicants

We received a total of 54 responses. Upon review, we identified and removed 4 duplicate entries, resulting in 50 unique records. Key Features in the Data:

a. Demographics: Name, Age, Gender, Class
b. Academic Background: Best subject, Worst subject
c. Technical Exposure:
   i. Heard of Data Analytics or Python?
   ii. Experience with Microsoft Excel?
   iii. Ability to operate a computer
   iv. Access to devices (phone, laptop)
d. Motivations & Previous Experience: Open-ended responses

4.1.1 Key insights from the preliminary analysis Put in overview

4.1.1.1 Gender distribution

The gender distribution of applicants (Figure 1) revealed a significantly high number of female applicants with a close count to that of their male counterparts. This suggests a growing interest among young women in pursuing careers in technology, especially when opportunities are made accessible and supported through inclusive communities. Such findings align with broader research indicating that when intentional outreach and community support mechanisms are provided, women show a strong inclination to engage with digital and technical fields (Sakpere et. al., 2023). This outcome supports ongoing efforts to close the gender gap in STEM (Science, Technology, Engineering, and Mathematics) education and careers in Africa (Sakpere et. al., 2023).

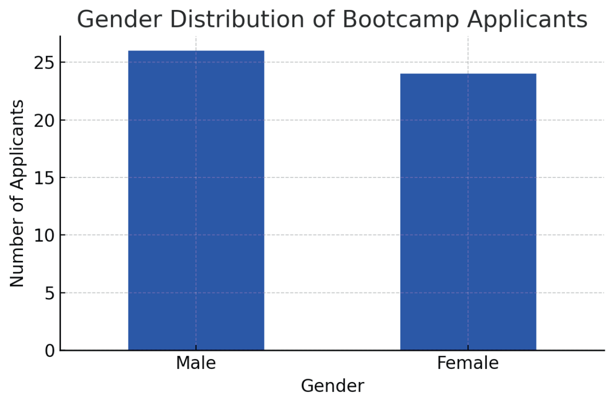

Figure 1 Gender distribution of the applicants (N = 50)

4.1.1.2 Familiarity with data analytics and python

Analysis of participants' responses regarding their prior knowledge of data analytics and Python programming (Figure 2) revealed that the majority had not previously encountered these concepts. This gap underscores the limited exposure to data science and computational thinking in the early stages of education, especially in Nigeria. Early introduction to coding and data literacy is increasingly recognized as essential for young people (Schanzer, 2022). The results highlight a critical need to embed such skills within school curricula and extracurricular programs.

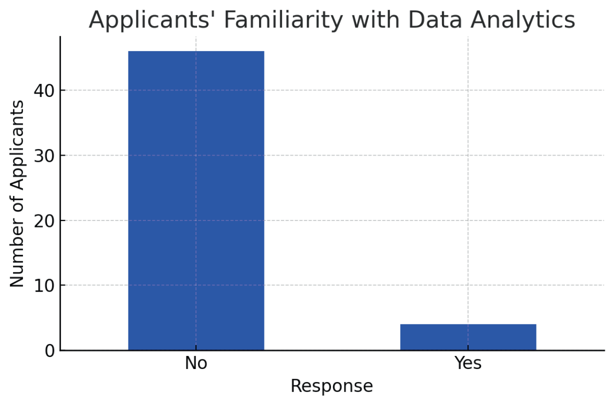

Figure 2 Applicants' level of familiarity with data analytics (N=50)

4.1.2.3 Computer operation skills

Encouragingly, a substantial proportion of the applicants reported basic computer operation skills (Figure 3). This foundational competency is essential for progressing to more advanced technical skills such as programming, data analysis, and digital design. Digital literacy, including basic computer use, is a key enabler of digital inclusion and lifelong learning. These results suggest that, despite limited exposure to specific tools like Python, students possess the necessary digital foundations for further upskilling.

4.1.2.4 Access to technology

The survey also assessed the participants' access to digital devices (Figure 4). Most students reported owning or having regular access to at least one digital device, predominantly smartphones. While this supports the feasibility of mobile-based learning platforms, it also suggests potential limitations when engaging in tasks that require more processing power or complex interfaces, such as software installation or advanced programming. The digital divide in terms of device capability and internet access remains a challenge in ensuring equitable access to quality digital education.

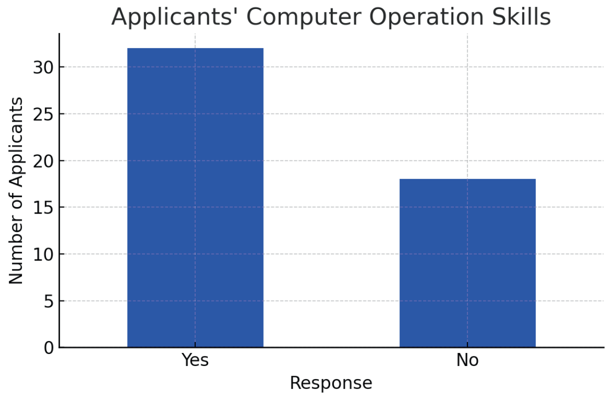

Figure 3 Applicants' computer operation skills (N = 50)

4.1.2.5 Motivations for application to attend the boot camp

Participants expressed diverse motivations for applying to the boot camp. Common keywords included *knowledge*, *learn*, *gain*, *computer*, *science*, *analytics*, *data*, and *certified*. These responses reflect a strong desire to acquire new skills, develop a deeper understanding of computing and data analysis, and achieve recognized qualifications. This enthusiasm is consistent with studies that identify intrinsic motivation and career aspirations as key drivers for youth engagement in STEM initiatives (Boekeloo, 2015; Lopez et. al., 2023)

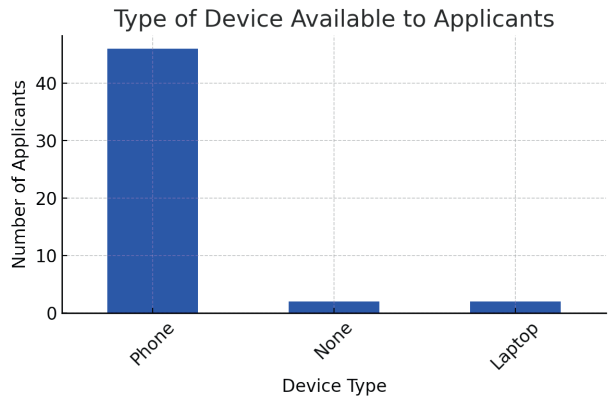

Figure 4 Applicants' access to device (N = 50)

4.1.2.6 Interest in mathematics

A noteworthy observation (Figure 5) was that most applicants indicated they were "very interested" in mathematics and working with numbers. This strong interest forms an excellent foundation for introducing data analytics, which relies heavily on mathematical reasoning, logical thinking, and quantitative analysis. The link between mathematical confidence and success in data science has been widely documented, further supporting the suitability of the selected cohort for such training.

4.2 Post-boot camp survey: engagement and learning outcomes

The post-boot camp survey captured 28 responses, primarily teenagers aged 14–18, with a single outlier aged 26. The dataset was further cleaned to remove duplicates and unmatched records from the pre-boot camp survey. After the cleaning, a total of 23 records were valid. The feedback collected comprised both quantitative Likert-scale ratings and qualitative, open-ended responses, offering a comprehensive view of the students' experiences, learning outcomes, and reflections. This mixed-methods approach supports a more nuanced understanding of the impact of short-term STEM interventions.

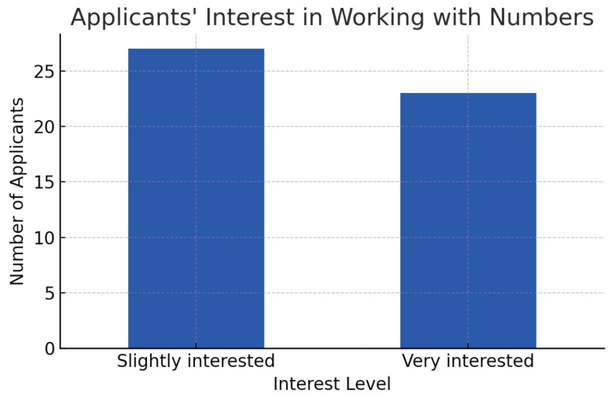

Figure 5 Interest in working with numbers (N = 50)

Feedback from the post-boot camp survey indicated a high level of satisfaction among participants with the content delivery, teaching methodology, and hands-on activities. Notably, a substantial number of students expressed enjoyment in the practical sessions that utilized Excel for data visualization. Interactive components involving pivot tables, dashboards, and simple Python scripts for data manipulation were consistently highlighted as especially impactful and transformative in shaping participants' understanding of digital tools.

Quantitative survey data supported these sentiments:

a. 87% of students rated the teaching style as either 4 or 5 on a scale of 5.

b. Another 87% of students rated the engagement as either 4 or 5 on a scale of 5

c. 69.6% rated their confidence in using Excel for data visualization as either 4 or 5 on a scale of 5

d. 100% of participants expressed a desire to attend future boot camps (including Yes and Maybe).

Table 1 summarizes the post-boot camp responses from participants. The engagement metrics have the highest rating. The corresponding question for this metric was: "How engaging did you find the activities and exercises?". This outcome suggests that the hands-on exercises and boot camp activities were impactful for the students.

Table 1: The quantitative summary of the post- boot camp survey (N = 23)

Metrics	Mean	Standard Deviation	Median
Excel Confidence	4.09	1.08	4
Teaching Style	4.17	1.11	4
Engagement Rating	4.39	1.16	5

These findings align with prior studies showing that short, intensive, and application-driven STEM experiences can significantly improve student motivation, engagement, and confidence in technical subjects (Sakpere, 2019). Active learning approaches are shown to outperform traditional lecture-based methods (Sakpere et. al., 2023).

4.2.1 Confidence and challenges

When asked to assess their confidence in using Excel for data visualization tasks, a large proportion (69.7%) of participants reported high confidence, scoring themselves 4 or 5 on a 5-point Likert scale. This confidence can be attributed to the hands-on, guided nature of the sessions and the immediate applicability of Excel skills to academic and real-life contexts.

However, Python programming was commonly cited as the most challenging aspect of the boot camp. Students requested more time and additional support in understanding the syntax and logic of programming. This aligns with literature noting that students—particularly novices—often struggle with abstract concepts in programming when they are introduced without sufficient scaffolding (Pechorina et. al., 2023).

To ease this transition, studies suggest integrating block-based programming environments, such as Scratch, as a bridge to more complex languages like Python (Sakpere & Adedeji, 2024). Such hybrid approaches reduce cognitive load and help learners build mental models of program structure and logic before diving into syntax-heavy environments.

4.2.2 Gender vs excel confidence and challenge perception

We further analyzed whether gender has an influence on the participants' confidence level in using Excel and their perception of challenges associated with acquiring data analytics skills. Specifically, participants' open-ended responses to the question *"What did you find most challenging?"* were reviewed for references to Python, analytics, dashboards, or project-related tasks—keywords indicative of core boot camp content.

Interestingly, both males and females had similar outcomes. As illustrated in Table 2, the male participants recorded slightly higher confidence in using Excel (difference of 0.15 on a scale of 5), and the female participants reported a slightly higher perceived challenge in learning data analytics skills (difference of 5.4%). This implies that gender is not really a significant factor in acquiring or learning data analytics skills. Thus, this study is vital for driving inclusion in the field of data science. This further highlight how thoughtfully designed interventions such as this boot camp can **effectively support learners of all genders** in developing data science competencies.

Table 2: Gender breakdown: excel confidence and data analytics challenge perception (N = 23)

Gender	Total Students	Avg. Excel Confidence	% Challenged by Analytics
Female`	10	4.00	70.0
Male	13	4.15	76.9

4.3 Comparative analysis of pre-boot camp analysis vs post-boot camp analysis

In this section, we compared the pre-survey responses with the post-survey responses. For the post-survey, we had 28 entries. This implies 78% responses post-boot camp. On cleaning the records, duplicates and invalid entries, including those not available in the pre-survey form, which sum up to 5, were excluded. In total, we had 23 valid matches that were used for the pre-boot camp and post-boot camp comparison and evaluation.

4.3.1 Confidence level in Excel

We compared prior Excel experience and post-boot camp confidence level in Excel of the 23 participants who responded to both the pre-survey and post-survey. 21 had no prior experience, while 2 had prior experience. As seen from Figure 6 and Table 3, the results show that those who had prior experience in Excel pre-boot camp had a slightly higher average confidence compared to those who did not have prior experience in Excel. However, the difference or the margin is a little. Precisely, the average confidence of those who had no prior experience in Excel is 4 on a scale of 5, while for those who have had prior experience it is 5 on a scale of 5. This implies that the boot camp was effective and well-designed even for beginners. The hands-on and project-based learning approach employed in the boot camp likely contributed to this.

Table 3: Prior experience in Excel vs post-camp average confidence

Prior Excel Experience?	Number of Students	Average Confidence (Post)
No	21	4.0
Yes	2	5.0

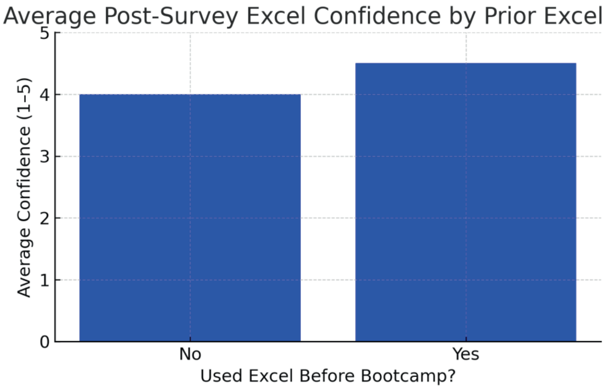

Figure 6Post survey Excel confidence vs prior use (N = 23)

4.3.2 Prior python awareness vs. post-camp perception of challenge

We compared the post-boot camp difficulty perception of programming in Python between those who had heard about it before the boot camp and those who had not. Our data on perceived Python difficulty was derived from responses to the open-ended question, "What did you find most challenging?". Of the 23 post-survey respondents, 15 explicitly commented on Python, while the remaining 8 identified other parts of the boot camp. As shown in Table 4, the two groups have very close difficulty perception, signifying that awareness did not significantly reduce the challenge of learning Python. On further analysis, it was observed that most of those who heard of Python before boot camp did hear about it either through a close associate or a seminar attended. This suggests that passive exposure does not necessarily lay a good foundation for learning programming. Our findings further reinforce that learning Python or programming in general remains a tough concept for most beginners, regardless of awareness and this justifies the need for continued hands-on reinforcement and simplification.

Table 4: Heard of Python before vs found Python challenging (N = 23)

Heard of Python Before	Total Students	Number Who Found Python Challenging	% Who Found Python Challenging
No	20	13	65.0%
Yes	3	2	66.7%

4.3.3 Correlation between prior exposure and engagement

To determine whether students' prior exposure to technical tools and knowledge influenced their engagement level during the boot camp, we analyzed key pre-survey questions alongside post-survey engagement ratings. Specifically, the pre-survey questions we focused on are whether participants had previously used Microsoft Excel, heard of the Python programming language, and heard of the concept of data analytics. Responses to each of these variables were recoded into a binary format, where "Yes" was assigned a value of 1 and "No" a value of 0. These were then correlated with the participants' post-boot camp responses to the question *"How engaging did you find the activities and exercises?"* using the **Pearson correlation coefficient**.

As shown in Table 5, results from the Pearson correlation coefficient indicate **weak but positive correlations** between prior exposure and perceived engagement. Even though students with some background in Excel, or knowledge of Python or data analytics, may have found the boot camp **slightly more engaging**, the effect was not substantial. Ultimately, students **without prior exposure** still reported **high engagement ratings**, indicating that the boot camp activities were accessible, well-structured, and inclusive of beginners. Our findings suggest that prior exposure to technical tools or basic knowledge of Python/data analytics is not a prerequisite for meaningful engagement. It's further noted that students with no previous experience rate the boot camp as highly engaging, emphasizing the accessibility and inclusivity of the designed intervention and the possibility of bringing diverse learners, regardless of background, into data literacy pathways.

Table 5: Result of Pearson correlation on the correlation between prior exposure and engagement level (N = 23)

Prior Exposure Type	Correlation Value	Correlation Interpretation
Used Microsoft Excel	0.17	Weak Positive
Heard of Python	0.21	Weak Positive
Heard of Data Analytics	0.21	Weak Positive

4.5 Thematic analysis of judges, instructor and mentor feedback

To complement the quantitative findings of this study, qualitative feedback was gathered from instructors, mentors, and judges involved in the data analytics boot camp. In total, there are 10 - 3 judges, 1 main instructor, 2 who served as both co-instructors and mentors and 4 who served exclusively as mentors. A thematic analysis was conducted to identify key patterns and recurring themes across the observations. The following five themes emerged:

a. *Student growth*

The mentors and the instructors noted that the boot camp had a great impact on students, especially those who had limited or no prior exposure to computers. As one mentor and instructor observed:

> *"Some started using the computer for the first, some second and they approached learning with the sense of humility and the hunger to know."*
>
> *"The bootcamp was an eye opener to most of them because most of them don't really know about Microsoft Excel…"*

The experience of designing and presenting data dashboards using Microsoft Excel was described as particularly impressive/transformative. Some comments from an instructor and a judge:

> *"I could witness the fulfillment on their faces as they presented their dashboards built in Microsoft Excel. I believe this has instilled in them a sense of ambition, determination and the pursuit of careers in technology.*
>
> *"The presentations were impressive (the dashboards created by the students)."*

These insights indeed show the potential of project-based learning in spurring interest in data science among high school students and fostering a sense of accomplishment.

These insights highlight the potential of experiential, project-based learning to spark interest in data science and foster a sense of accomplishment among students.

b. *Technical barriers and learning gaps*

Despite the success of the boot camp, mentors identified that technical challenges, such as limited access to computers, affected the learning process. In most cases, students worked in groups with three or four participants sharing a single device, which restricted hands-on learning opportunities. One mentor and judge remarked:

> *"The laptops we had meant people were grouped and most groups had more than 3 persons per laptop. I noticed most times it's the same person or same set of people, generally those already good, that did the typing."*
>
> *"Students/computer ratio is high. If possible reduce the number of students to 2 per computer for effective learning & teaching."*

In addition, many students had limited computer literacy, which made it difficult for them to fully engage with the technical content. One instructor/mentor reflected:

> *"While the topic we covered was very relevant and timely, I observed that many of the students were not very familiar with using a computer. It might be helpful to introduce a session focused on basic computer literacy in the next boot camp."*

These findings suggest that future interventions should consider incorporating introductory sessions on basic computing skills to ensure all participants can fully benefit from the program.

c. *Challenges with verbal expression and communication*

The judges observed that while students demonstrated understanding of the content, many struggled to articulate their thoughts during presentations. This was not necessarily a reflection of poor comprehension, but rather of low confidence or limited practice with formal communication. Some comments:

> *"The students had a good understanding of what they were taught, but I noticed many had trouble putting their thoughts into words. They struggled with expression."*
>
> *"Each group had that one vocal person, the leader, but when others were asked questions, they struggled to respond."*
>
> *"With the presentation, all the students were not really prepared except for one or two who spoke about the work."*

This theme highlights the importance of supporting not just technical learning, but also students' communication and presentation skills, particularly in group-based and project-driven environments.

d. *Emotional and motivational outcomes*

The boot camp had a strong emotional and motivational impact on many students. Many students expressed interest in pursuing careers in technology and sought guidance on their future aspirations. As one mentor recounted:

> *"I spoke about how whatever they desire they are capable to try for it... Afterwards a couple of them came to meet me to share concerns they had about the future and asked for advice. I realized they need guidance honestly and encouragement."*

These reflections underscore the role of boot camps not only as learning experiences but also as platforms for mentorship and personal growth.

e. Program design and recommendations for future implementation

Instructors and mentors offered practical recommendations to enhance the effectiveness of future boot camps. These included ensuring individualized access to laptops, incorporating foundational computing sessions, and introducing long-term projects that would extend learning beyond the duration of the camp. One mentor suggested:

> *"One feedback for upcoming boot camps might be: if there's a way to incorporate long-term projects that they can work on and report to their teachers... so they won't learn something, abandon it for 7 months, and come back to relearn it."*

Another instructor/mentor proposed:

> *"We could consider sending out a short form to assess their current understanding of tech, computer science, and related fields. This would allow us to create content to their specific needs."*

These suggestions point to the need for continuous refinement of instructional design based on learner readiness and context.

4.6 Memorable moments and self-discovery

Beyond technical training, the boot camp incorporated enriching moments that fostered self-awareness, reflection, and aspiration. Many students highlighted experiences such as being named among the top performers and receiving peer and mentor recognition as defining and motivational. Additionally, the opportunity to tour various university departments exposed students to academic disciplines and potential future career paths.

One of the most praised components was the self-discovery session, which involved guided reflections on personality traits, interests, and long-term goals. This session was especially impactful in helping students align personal strengths with academic and professional aspirations. Incorporating such reflective practices within STEM education is vital to developing not just cognitive skills but also emotional intelligence and a sense of purpose. By addressing both the technical and affective dimensions of learning, the boot camp presented a holistic model of STEM education.

4.7 Implications and reflections

The overall success of the boot camp affirms the value of short-term, hands-on learning experiences in improving students' technical competencies and enthusiasm for STEM. The integration of tools like Excel and Python not only facilitated learning but also allowed students to explore real-world applications of data analytics. Furthermore, the unanimous interest in future participation underscores the program's relevance and resonance with the participants.

However, the challenges associated with Python instruction suggest that differentiated learning pathways possibly involving visual tools like Scratch, may be necessary to support novice learners (Sakpere & Adedeji, 2024). The inclusion of mentorship, recognition, and self-exploration components further enriched the program, creating a supportive and inspiring environment for emerging technologists.

4.8 Study

A major limitation of this study has to do with the sample size of students who participated in the boot camp and completed the pre-boot camp survey/application and post-camp survey. In addition, the participants are limited to a particular region of Nigeria, limiting the generalizability of the findings to broader populations across Africa or similar contexts.

Though, through the additional use of qualitative responses and assessments from mentors, judges and instructors, the results and insights from the study are improved, it does not fully substitute for formal objective measurement of learning gains.

Despite these limitations, the findings offer important insights into the design and feasibility of introductory data analytics interventions for high school students in underserved communities.

5. CONCLUSION

In this study, we presented the design, implementation, and evaluation of a five-day data analytics boot camp targeted at equipping Nigerian secondary school students with basic data analytics skills. Through a combination of pre- and post-surveys, participant project work, and qualitative reflections from judges, mentors and instructors, we found out that prior exposure to data analytic tools or information/knowledge had limited influence on students' ability to engage with the content of the boot camp. Even students with no prior experience demonstrated comparable levels of confidence and enthusiasm in the post-boot camp. While programming in Python remained a challenge for many, the boot camp still succeeded in sparking curiosity and instilling basic data analytics skills/knowledge. Qualitative analysis of feedback from mentors, instructors and judges resulted in 5 themes that indicated student growth, technical challenges, need for communication skills, importance of emotional and motivational support and actionable recommendations for future boot camp.

Overall, the boot camp presents a model that is scalable and inclusive to build human capacity in the field of data science among African secondary school students. We believe that with continuous refinement and support from various stakeholders in the field of education, technology and policy, short-term interventions such as this can have a long-term impact on the future of STEM education in Africa. This work contributes to the discourse on STEM education in Africa and offers a replicable model for similar interventions aiming to bridge the digital divide and prepare youth for the demands of the data economy.

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