PREDICTING POSITIVE OUTCOMES IN A PROJECT-BASED INTRODUCTORY STATISTICS COURSE: A STUDY OF UNDERGRADUATE STUDENTS IN GHANA

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ABSTRACT

This study examines the impact of the Passion-Driven Statistics curriculum in an introductory statistics course at a private university in Ghana, West Africa. The curriculum employs a project-based approach, allowing students to develop and investigate their own research questions using large datasets and statistical software. The study evaluates how students' background characteristics, prior academic experiences, and engagement in the course predict positive learning outcomes. Pre- and post-course survey data from 328 students (58.2% women, 41.8% men) were analyzed to assess changes in research skills, confidence, and interest in statistics. Results indicate that engagement with the course and instructional support were strongly associated with gains in thinking and working like a scientist, personal research-related growth, and positive attitudes toward statistical inquiry. While men reported higher confidence in programming at the start of the course, women demonstrated similar levels of engagement and positive post-course outcomes. The findings highlight the potential of project-based statistical education to foster inclusive learning environments and enhance student confidence in data analysis, contributing to broader efforts to improve quantitative education in diverse global settings.

Keywords: *Statistics education research; Project-based learning; African higher education; Passion-Driven Statistics*

1. INTRODUCTION

Introductory statistics courses today face many demands. Beyond teaching foundational descriptive and inferential concepts and habits of statistical reasoning, the introductory course should equip students with skills in data management and statistical computing, motivate statistical learning among students of various majors, and address inequalities in research, quantitative skill development, and participation in data-related and STEM fields (American Statistical Association–Mathematical Association of America Joint Committee on Undergraduate Statistics, 2014; GAISE College Report ASA Revision Committee, 2016; LaLonde et al., 2024). The introductory course helps future researchers from across the natural and social sciences understand the scientific method, how hypotheses are formulated and tested, and how outcomes of quantitative research are interpreted and reported. Additionally, knowledge of statistics supports important tenets of democratic citizenship in an era of ubiquitous data, where ethical concerns regarding sources of data, access to data, and uses of data abound (American Statistical Association, 2022; Souza et al., 2020; Ridgway, 2022).

To meet these demands, a movement in statistics education is underway to center experiences with data and to emphasize the use of computing to learn statistics and probability concepts over algebraic or formulaic approaches (GAISE College Report ASA Revision Committee, 2016; LaLonde et al., 2024; Neumann et al., 2013; Stern et al., 2020). To address inequalities in developing data-oriented skills and to motivate statistics learning among students from diverse disciplines, inquiry-based projects have been advocated as an approach for introductory statistics courses (Garfield & Ben-Zvi, 2007; Lee & Ban, 2022). Project-Based Learning (PBL) refers broadly to instructional approaches in which students learn through extended inquiry organized around authentic questions or problems, often culminating in a concrete product or presentation. Project-based approaches have been shown to improve motivation, learning outcomes, and course experiences in statistics among students from various disciplines and socio-cultural and academic backgrounds (Khalemsky & Stukalin, 2024; Rosenbaum & Dierker, 2024; Spence et al., 2022; Wickramasinghe & Appiah, 2024).

Despite growing evidence supporting project-based and data-centered approaches in statistics education, most published research has been conducted in North American and European contexts. Much less is known about how these approaches function in sub-Saharan African higher education, where students typically enter university from more traditional, exam-oriented instructional environments; hold views of mathematics shaped by abstract and procedurally orientated curricula; and have limited practical experiences with data (Akyeampong et al., 2013; Bethell, 2016; North et al., 2014). In such contexts, introductory statistics courses are frequently experienced by students as abstract and symbolic, contributing to anxiety and disengagement (Silva & Sarnecka, 2025). Understanding how project-based approaches operate in these settings is therefore critical for evaluating their broader applicability and potential to support student learning across diverse educational environments.

One instructional model that may support students in sub-Saharan Africa in their transition to data-centered, inquiry-driven approaches is Passion-Driven Statistics, a project-based, data-and-computing-driven curriculum originally developed and evaluated in United States higher education settings (Dierker et al., 2012; Spence et al., 2022). Unlike many PBL implementations that organize students around shared or instructor-defined problems, Passion-Driven Statistics centers on individually chosen research questions and personalized analytic decisions, resulting in partially unique learning trajectories for each student (Chin et al., 2002). This emphasis on student-generated questions and learner agency aligns with constructivist and inquiry-based learning theories, which suggest that students develop deeper conceptual understanding when they actively construct knowledge through meaningful inquiry (Buchanan et al., 2016; Kaiser et al., 2018). In statistics education, such approaches have been associated with improved conceptual understanding and engagement relative to more traditional instructional methods (Garfield & Ben-Zvi, 2008).

The Passion-Driven Statistics curriculum centers on authentic research projects using real-world datasets and statistical software. Students generate hypotheses, conduct literature reviews, prepare and analyze data, and interpret and present findings through an iterative process that mirrors real-world statistical practice. Instructional support is structured through staged assignments and "just-in-time" guidance, allowing students to build independence while engaging in complex analytic tasks (Budé et al., 2011; Lombard & Schneider, 2013).

Prior research in U.S. contexts indicates that Passion-Driven Statistics is associated with increased engagement, confidence in working with data, and sustained interest in research and data-related coursework (Dierker et al., 2015, 2016, 2018; Nazzaro et al., 2020). These findings are consistent with a broader body of research on course-based undergraduate research experiences (CUREs) and project-based learning, which have documented gains in student engagement, confidence, and persistence in science, technology, engineering, and mathematics (STEM) disciplines (Auchincloss et al., 2014; Corwin et al., 2015; Sharma & Gupta, 2026).

In addition to its focus on student-centered learning, project-based statistics education may have implications for equity in participation and outcomes. Women remain underrepresented in research and STEM—in Africa and globally—and differences in prior experience and self-efficacy can shape women's engagement with quantitative disciplines (Elu & Price, 2017; Fisher et al., 2020; Founou et al., 2023; Kyaruzi, 2023; Luneta & Sunzuma, 2022; Quarshie et al., 2023; UNESCO Institute for

Statistics, 2022a; UNESCO Institute for Statistics, 2022b). Instructional approaches that emphasize relevance, autonomy, and mastery experiences, key features of PBL, may support more inclusive learning environments by fostering engagement and confidence across diverse student groups.

In the present study, gender is examined in two distinct but related ways. First, broader disparities in women's participation in research and STEM fields in Africa motivate the importance of inclusive instructional approaches. Second, we empirically examine whether women and men differ in their course experiences, outcomes, and predictors of those outcomes within a project-based statistics course. The study does not attempt to explain structural gender disparities but rather evaluates whether this instructional model supports comparable engagement and learning-related gains across genders.

The present study evaluates the implementation of the Passion-Driven Statistics curriculum in an introductory statistics course at a private university in Ghana. The tertiary education system in Ghana consists of large, publicly funded research universities, smaller private universities (a mix of religiously affiliated, not-for-profit, and for-profit institutions), and public technical universities. The present study takes place in a not-for-profit private university with a student population of 1,500 students. The primary aim is to assess student engagement and learning-related outcomes associated with this project-based, data-centered approach. A secondary aim is to examine whether these experiences and outcomes differ by gender and whether the predictors of these outcomes operate similarly for women and men. Accordingly, the study addresses the following research questions: (1) To what extent do students report engagement and learning-related gains in a Passion-Driven Statistics course? (2) Which student background characteristics and course experiences predict these gains? and (3) Do these experiences, outcomes, and their predictors differ by gender?

2. METHODS

2.1. CONTEXUALIZATION OF THE PASSION-DRIVEN STATISTICS MODEL

The Passion-Driven Statistics model is delivered in the context of research projects of students' own choosing, using publicly available secondary data. The curriculum focuses on the decisions and skills involved in asking and answering questions with data and telling accurate and compelling data stories. To accomplish this, students in Ghana were provided with two or more datasets and corresponding data dictionaries or allowed to source their own datasets from online sources with approval. Datasets provided to students over the period of the study include Afrobarometer multi-country data, Ghana Demographic and Health Survey, GeoPoll Africa data, internationally comparative data from Our World in Data, international sports data, Ghana Living Standards Survey, and European Social Survey data.[1] Based on the student's choice of data, each student generated testable hypotheses, conducted a review of related literature, prepared data for analysis, selected and used descriptive and inferential statistical tools, and evaluated, interpreted, and presented research findings in a final poster or manuscript format.

The course was structured as a 14-week semester-long class meeting twice weekly for a 1.5-hour, interactive lecture and discussion, plus a weekly 1.5-hour lab session facilitated by course teaching assistants (TAs). The course was required for all students, who were a mix of second-year Business Administration, Computer Science, Management Information Systems, and Economics majors. Class sizes were between 50 and 70 students. A flipped classroom approach was used, where students were expected to go through statistics and probability content online, while class time consisted of hands-on simulations and scaffolding activities and time devoted to individual projects, with the course instructor and TA functioning as mentors rather than lecturers.[2] One weekly lab session, instructor and TA office hours, and small-group meetings provided individualized support for assignments, coding challenges, and project work.

[1] Selected data links. Afrobarometer surveys: https://www.afrobarometer.org/surveys-and-methods/survey-resources/. Ghana Demographic and Health Survey (2022): https://microdata.worldbank.org/index.php/catalog/6122. Ghana Living Standards Survey Round 7: https://microdata.statsghana.gov.gh/index.php/catalog/97.

[2] Students accessed probability and statistics content online from Carnegie Mellon Open Learning Initiative's Probability and Statistics Course (https://oli.cmu.edu/courses/probability-and-statistics/).

The semester-long project was broken down into five staged assignments, including the final poster presentation or manuscript submission. Students received feedback on each interim assignment with the expectation that they would use the feedback to refine and improve their work. The first project assignment asked students to examine a published article involving survey research, typically based on one of the datasets made available to students for the project (e.g., Cheeseman, 2014; Mishra et al., 2007), choose a dataset for their project, and attempt the first iteration of their research question. Students were guided to read empirical research articles with attention to research questions, study design, measurement, and analytic strategies. Class time included brief instruction on how to identify key components of a research article and evaluate how authors use data to support claims. Students are then tasked to develop their initial research question, review the data-dictionary for their chosen dataset, and to justify their initial choice of variables.

The second project assignment guided students through searching for empirical studies related to their topic, how to use citation management software, and effective notetaking. Students submitted an annotated bibliography and a second iteration of their research question. The third project assignment guided students through exploratory data analysis using their chosen dataset, including identifying explanatory and response variables; cleaning, recoding, and subsetting data; and generating descriptive statistics and visual displays. Students completed these activities using RMarkdown and submitted knitted RMarkdown files for feedback. Project assignment four guided students through generating bivariate graphs and appropriate inferential statistical tests for two or three associations related to their research question. In addition to knitted RMarkdown files, students submitted a written summary of the results of their hypothesis tests and an initial conclusion about their research question. The final project assignment gave students guidance on interpreting and accurately communicating the outcomes of their research, how to tell engaging data stories, and the format and expectations of the final submission.

Collectively, these structured tasks aligned with project-based learning (PBL) principles. Class time alternated between short skills-focused instruction and periods of supported project work, and students received actionable feedback on interim submissions throughout the student-directed research process (Buchanan et al., 2016; Sharma & Gupta, 2026). Key PBL elements of the research project included: (a) student choice of research question and dataset; (b) iterative cycles of analysis, feedback, and revision; (c) opportunities for reflection on decisions and challenges; and (d) public sharing of results through poster or manuscript presentations—core features identified in PBL research (Lombard & Schneider, 2013). This sequence ensured that statistical methods were introduced "just in time," as tools students needed to answer their own research questions rather than as abstract topics taught in isolation, consistent with inquiry-based and problem-based learning frameworks (Budé et al., 2011). The model, therefore, positioned students as active investigators applying statistics in authentic contexts rather than passive recipients of content (Kaiser et al., 2018).

2.2. PARTICIPANTS

Pre- and post-course survey data were examined from 328 students enrolled in an introductory statistics course (in 2019, 2023, and 2024) using the Passion-Driven Statistics model at a private university in Ghana, West Africa. The sample included 191 (58.2%) women and 137 (41.8%) men. Based on admissions data, about 75% of students from these year groups were from Ghana and 25% from other African countries, while about 32% received full financial aid, 15% received partial financial aid, and 30% were first-generation college students. All students had access to laptop computers. The pre-course survey was completed prior to the end of the second week of classes, and the post-course survey was completed during the last weeks of the semester. Each survey took approximately 10 to 15 minutes to complete. Because the introductory statistics course is a degree requirement for students majoring in Business Administration, Computer Science, Management Information Systems, and Economics, participants were drawn from these four programs. The university does not offer majors in mathematics or statistics, while students majoring in engineering majors take a separate engineering statistics course.

2.3. MEASURES

2.3.1. DEMOGRAPHICS AND ACADEMIC BACKGROUND CHARACTERISTICS

The pre-course survey included questions assessing age and gender. Academic background was assessed by questions about having taken a previous statistics course, any prior programming experience, e.g., R, SAS, Stata, Python, C++, Java, HTML, etc. (yes/no), and self-confidence when it comes to learning programming from 1 (strongly disagree) to 5 (strongly agree). Self-perceived skills in mathematics were measured by the question, "How good at mathematics are you?" on a scale from 1 (very poor) to 5 (very good). Anxiety about the course was assessed using a single item, "The thought of being enrolled in this course makes me nervous," rated from 1 (strongly disagree) to 5 (strongly agree). This item is drawn from the Statistics Anxiety Rating Scale (SARS), a widely used measure with established validity and reliability (Onwuegbuzie & Wilson, 2003; Wise, 1985). We selected this item as a brief indicator of anticipatory statistics anxiety to minimize survey burden in a multi-scale questionnaire administered in a classroom context. Prior research indicates that single-item measures can serve as reasonable proxies for domain-specific affect when the construct is narrow and clearly defined (e.g., Bergkvist & Rossiter, 2007). Accordingly, this item should be interpreted as a general indicator of statistics-related anxiety rather than a comprehensive assessment of the construct.

Items from the Classroom Undergraduate Research Experience Survey (CURE) were included in the pre-course survey to measure *prior experience with research* (Auchincloss et al., 2014). Areas of experience include conducting a quantitative project entirely of your own design, reading primary source scientific literature, collecting data, analyzing data, and presenting a poster at a science or research poster session. Response options ranged from 1 (no experience or feel inexperienced) to 5 (extensive experience or mastered this element). A mean score was calculated as an aggregate measure of previous research experience (Lopatto et al., 2008). The five-item scale demonstrated good internal consistency in the present sample (Cronbach's $\alpha = .81$).

2.3.2. STUDENT EXPERIENCES IN THE COURSE

Items on the satisfaction scale from the Undergraduate Research Student Self-Assessment (URSSA) were administered in the post-course survey (Hunter et al., 2009; Weston & Laursen, 2015). Students rated their working relationship and the amount of time spent with their instructor, teaching assistant, or peer mentors. Response options ranged from 1 (poor) to 5 (excellent) and were averaged to create an aggregate measure of support. The five-item scale demonstrated good internal consistency in the present sample (Cronbach's $\alpha = .81$).

Students' perception of course rigor was measured by the question, "How challenging did you find this course?" from 1 (not at all) to 5 (the most challenging).

Questions addressing *student engagement* were drawn from the survey used by Gasiewski et al. (2012). Areas assessed included: asking questions in class, discussing course grades or assignments with the instructor, attending the instructor's office hours, tutoring other students in the course, preparing for class sessions by completing assigned readings and/or videos, reviewing class materials before they were covered, attending review or help sessions to enhance understanding of course content, studying with students from the course, and participating in class discussions. Response options ranged from 1 (never) to 5 (always). Items were averaged to create an aggregate measure of students' engagement. The scale demonstrated good internal consistency in the present sample (Cronbach's $\alpha = .75$).

2.3.3. COURSE OUTCOMES

Core scales from the URSSA were used to measure self-reported gains in thinking and working like a scientist (e.g., analyzing data for patterns and identifying limitations of research methods), personal gains related to research (e.g., ability to contribute to science, comfort discussing scientific concepts and patience in the slow pace of research), gains in research skills (e.g., preparing a scientific presentation and keeping a detailed lab notebook) and positive attitudes and behaviors as a researcher (e.g. feeling like a scientist, feeling responsible for the project and feeling part of a scientific community). Previous research has shown that the URSSA represents separate but related constructs from the CURE survey. Average scores form reliable, moderate to highly correlated composite measures. URSSA scales have been shown to correlate with ratings of satisfaction with external aspects of the research experience (Hunter et al., 2009; Weston & Laursen, 2015). Response options ranged from 1 (none) to 5 (a great deal). Items were averaged to create aggregate measures for each scale. Composite variables exceeded accepted standards for reliability (i.e., alpha > 0.80).

Students were asked additional questions in both the pre and post course surveys pertaining to their interest in conducting research from 1 (not at all interested) to 5 (extremely interested) and likelihood/intention of (a) pursuing advanced coursework in statistics or data analysis (b) taking any statistics or data analysis courses in the future from 1 (definitely not) to 5 (definitely yes), (c) using statistics as they complete the remainder of their degree program and (d) using statistics in the field in which they hope to be employed when they finish school from 1 (never) to 5 (frequently). The scale demonstrated excellent internal consistency in the present sample (Cronbach's $\alpha = .91$). Responses on the pre-survey were subtracted from responses to the same post-survey questions, and dichotomous variables were created and averaged to indicate the proportion of responses indicating an increase among the five pre/post items.

2.4. ANALYSES

Chi-square tests of independence and ANOVA were used to evaluate differences by gender for categorical and continuous variables, respectively. Next, multiple linear regression analysis was used to explain variation in each outcome measure for men and women. Individual background characteristics and course experience were used as predictors in each regression model. The results are shown as standardized coefficients (beta). Cases with missing data were deleted listwise.

All analyses were conducted using SAS version 9.4 (SAS Institute, Cary, NC). Descriptive statistics were first computed to summarize sample characteristics and to inspect for outliers and data entry errors. Gender differences were first explored using one-way ANOVA for continuous variables and chi-square tests for categorical variables. Because several predictors and outcomes were measured on five-point Likert-type scales, mean scores were treated as continuous variables.

To examine the relationships between student characteristics, course experiences, and course outcomes, a series of multiple linear regression models were estimated separately for women and men. This stratified analytic approach allowed us to evaluate whether the same predictors operated similarly across gender groups, given evidence of gendered pathways in research and STEM engagement. Separate models were estimated for each of the five outcome variables: (a) gains in thinking and working like a scientist, (b) personal gains related to research, (c) gains in research skills, (d) positive attitudes and behaviors as a researcher, and (e) increases in interest and intentions to use statistics in the future.

Predictor variables included students' age, prior statistics course (yes/no), prior programming experience (yes/no), self-confidence in learning programming, self-rated mathematics skill, anxiety about the course, prior research experience, perceived course challenge, engagement, and instructional support. All continuous predictors were standardized prior to analysis to facilitate the interpretation of standardized coefficients (β). Each model thus estimates the unique contribution of background and course experience variables to variation in each outcome measure while controlling for the other predictors.

Statistical significance was evaluated using an alpha level of .05. Standardized beta coefficients and associated p-values are presented in Table 3. Model fit was assessed using adjusted R^2 values. As a robustness check, pooled models including all students were estimated with gender entered as a covariate and interaction terms for gender × key predictors; patterns of significance were consistent with the stratified results reported here.

3. RESULTS

3.1. BACKGROUND CHARACTERISTICS AND COURSE EXPERIENCES BY GENDER

Background characteristics and course experiences are presented in Table 1. Women and men enrolled in the introductory statistics course using the Passion-Driven Statistics model were equally likely to have prior programming experience. They also reported similar levels of mathematics skills and experience with research. Men, however, were a few months older than women on average and reported higher levels of self-confidence in learning programming. Men were also more likely to have taken a prior statistics course and reported being less nervous about being enrolled in the present course.

Based on the post-course survey, engagement in the Passion-Driven Statistics curriculum, the amount of instructional support received, and ratings of course difficulty were statistically similar for women and men.

Table 1. Demographic and academic background characteristics by gender[1]

Pre Survey	Women N=191	Men N=137	Statistics[2]
Age	19.3 (1.04)	19.8 (1.49)	F(1,320)=8.4, p=.004
Prior statistics course	73 (38.2%)	68 (49.6%)	X^2=4.24, df=1, p=.04
Prior programming experience	156 (82.1%)	111 (82.2%)	n.s. (p = .98)
I have a lot of self-confidence when it comes to learning programming (1=str disagree to 5=str agree)	2.8 (0.88)	3.4 (1.04)	F(1,324)=32.9, p=.0001
How good are you at mathematics? (1=v poor to 5=v good)	3.8 (0.76)	3.8 (0.77)	n.s. (p =.79)
The thought of being enrolled in a statistics course makes me nervous (1=str disagree to 5=str agree)	2.8 (1.06)	2.5 (0.97)	F(1,323)=4.98, p =.03
CURE prior research experience	2.4 (0.76)	2.5 (0.76)	n.s. (p=.16)
Post Survey			
How challenging did you find the course (1=not at all to 5=extremely challenging)	3.1 (0.76)	3.2 (0.75)	n.s. (p=.10)
Engagement with the course	3.2 (0.59)	3.2 (0.66)	n.s. (p= .60)
URSSA instructional support	3.2 (0.57)	3.2 (0.60)	n.s. (p=.70)

[1] Mean (s.d.) presented for quantitative variables and n (%) presented for binary variables.
[2] Analyses and associated statistics are based on the number of respondents completing each item or scale.
n.s. indicates p>.05

3.2. COURSE OUTCOMES

Course outcomes for women and men are presented in Table 2, including gains in thinking and working like a scientist (e.g., analyzing data for patterns, identifying limitations of research methods), personal gains related to research (e.g., ability to contribute to science, comfort discussing scientific concepts, patience in the slow pace of research), gains in research skills (e.g., preparing a scientific poster, keeping a detailed lab notebook), gains in positive attitudes and behaviors as a researcher (e.g. feeling like a scientist, feeling responsible for the project, feeling part of a scientific community). Finally, the proportion of positive increases in interest/intentions was statistically similar for women and men.

Table 2. Course outcomes by gender[1]

	Women N=191	Men N=137	Statistics[2]
Thinking like a scientist	4.2 (0.74)	4.1 (0.72)	n.s. (p=.75)
Gains related to research	3.9 (0.78)	3.9 (0.69)	n.s. (p=.55)
Gains in research skills	3.9 (0.78)	4.0 (0.78)	n.s. (p=.93)
Positive attitudes and behaviors	3.5 (0.92)	3.6 (0.87)	n.s. (p=.48)
Rate of increase in interest/intention[3]	0.30 (0.30)	0.32 (0.31)	n.s. (p=.83)

[1] Mean (s.d.) presented for quantitative variables – response options for gains ranged from 1 (none) to 5 (a great deal) – and n (%) presented for binary variables.
[2] Analyses and associated statistics are based on the number of respondents completing each item or scale.
n.s. indicates p>.05
[3]Proportion of responses indicating an increase among the five pre/post items

Next, multivariate regression models were run to evaluate student background characteristics and course experiences that predict positive course outcomes for women and men (Table 3). For both women and men, level of engagement in the course and satisfaction with instructional support were associated with greater gains on each URSSA subscale (thinking and working like a scientist, personal gains related to research, research skills, positive attitudes and behaviors as a researcher). Engagement in the course also predicted an increase in interest/intention to use statistics in the future, but only for men.

Confidence in learning to program when entering the course predicted gains in positive attitudes and behaviors for women and increased interest/intention to use statistics in the future for men. Though prior programming experience predicted gains related to research for women, the lack of programming experience predicted gains in positive attitudes and behaviors in men. Further, men who found the course *less* challenging reported greater gains on the URSSA subscales of thinking like a scientist and positive attitudes and behaviors. Finally, for men, increased nervousness about being enrolled in the course predicted increased interest/intention to use statistics in the future.

Table 3. Multiple regression models predicting each course outcome (beta coefficient) for women and men.

	Thinking like a scientist (URSSA)		Research gains (URSSA)		Research skills (URSSA)		Positive attitudes/ behaviors (URSSA)		Increase in interest/ intention[1]	
	women	men	women	men	women	men	women	men	women	men
Age	0.00	-0.02	0.04	-0.01	0.01	0.01	0.07	0.05	-0.03	0.00
Prior statistics course	-0.04	0.05	-0.10	0.03	0.08	0.01	-0.02	0.14	0.04	-0.08
Prior programming experience	0.01	-0.08	0.30*	-0.04	0.16	-0.01	0.15	-0.37*	0.06	-0.05
I have a lot of self-confidence learning programming	0.07	0.08	0.13	0.04	0.05	0.03	0.15*	0.09	0.04	0.10**
How good at mathematics are you?	0.04	0.03	0.08	0.13	-0.06	0.13	-0.04	0.10	-0.02	-0.04
The thought of being enrolled in a statistics course makes me nervous	0.01	-0.02	0.01	-0.04	0.02	-0.01	0.03	0.09	0.04	0.11***
Prior research experience	0.02	0.12	0.01	0.06	0.02	0.10	0.10	0.04	-0.03	-0.02
How challenging did you find the course	-0.05	-0.16*	0.02	-0.13	-0.03	-0.12	0.07	-0.17*	-0.04	-0.06

Engagement with the course	0.38**	0.48***	0.30**	0.49***	0.33**	0.48***	0.27**	0.55***	0.05	0.17***
URSSA instructional support	0.26***	0.33**	0.48***	0.45***	0.47***	0.32**	0.53***	0.56***	0.02	-0.02

[1]Proportion of responses indicating an increase among the five pre/post items
*p<.05; ** p<.01; *** p<.001

4. DISCUSSION

The present study examined the implementation of the Passion-Driven Statistics curriculum in an introductory statistics course at a university in Ghana, West Africa. We have described in previous reports the development of the Passion-Driven Statistics initiative, its success in the U.S. of attracting higher rates of under-represented students compared to a traditional math statistics curriculum (Dierker et al., 2012; Dierker et al., 2015), and its role in influencing future course choices (Nazzaro et al., 2020) and career trajectories (Dierker et al., 2024). A central goal of this study was to evaluate the feasibility and student outcomes of implementing Passion-Driven Statistics in a new national and institutional context. A secondary, but conceptually important, goal was to examine gender equity: whether women and men report comparable course experiences and learning-related gains, and whether the predictors of those gains differ by gender. Findings suggest that the project-based, data-and-computing-driven approach is associated with strong learning-related gains overall, and that women and men reported comparable engagement and outcomes across the domains assessed (URSSA subscales and interest/intentions). These results indicate that the curriculum effectively supports students taking introductory statistics in Ghana, offering evidence of the adaptability of the project-based approach in a regional context different from the U.S.

Although men initially reported greater confidence in learning programming, both men and women engaged similarly with the Passion-Driven Statistics (PDS) curriculum and expressed comparable satisfaction with instructional support. These results suggest that initial differences in self-perceptions of ability did not translate into differences in engagement or learning-related outcomes. The PDS model appears to support an environment in which women and men report similar engagement, instructional support, and gains in research-related skills and scientific thinking. These results are consistent with prior studies showing that the curriculum increases students' confidence in working with data, conducting research, and applying statistical concepts across diverse populations (Dierker et al., 2015, 2018).

Engagement with the course and satisfaction with instructional support were strong and consistent predictors of positive learning outcomes for both men and women. These results reinforce the importance of active participation and individualized feedback in statistics education (Li & Xue, 2023). In the present study, such engagement occurred primarily through the weekly lab sessions led by TAs, attending office hours, and making small-group appointments with instructors and TAs. These structured opportunities for interaction contributed significantly to students' gains in scientific thinking, research skills, and positive attitudes toward statistics. The consistency of these effects across gender supports a growing body of literature emphasizing that interactive, student-centered approaches benefit all learners, regardless of background or prior experience (Xu et al., 2023; Silva & Sarnecka, 2025).

Previous research, along with the present findings, underscores the positive relationship between engagement and self-efficacy in statistics education. As students engage more deeply with practical, contextually relevant tasks, they experience greater mastery and confidence, which in turn fosters continued engagement—a positive feedback loop central to effective learning. A review of computing education studies in Africa reached a similar conclusion, noting that students are more likely to engage with and retain computing knowledge when it is presented within a familiar and meaningful context (Hamouda et al., 2025). In this light, the strong associations between engagement, instructional support, and course outcomes suggest that the PDS approach supports learning for students broadly, including those who may begin with lower confidence in quantitative domains (Kyaruzi, 2023).

Gender differences in the direction of some associations also emerged. For women, prior programming experience predicted greater gains in research-related outcomes, whereas for men, the lack of prior programming experience was linked to gains in positive attitudes and behaviors as researchers. This pattern suggests that early exposure to computing may serve as a confidence booster for women, while men without prior experience may experience greater perceived growth when they succeed in a new and initially intimidating domain. Notably, all students in this Ghanaian sample had previously completed an introductory computing course, which may have contributed to the relatively high baseline levels of programming exposure observed in both groups and the small gender differences in prior programming experience. Expanding early structured exposure to statistical research alongside programming may help support students with varying levels of prior experience. Importantly, these results suggest that equity is not only a question of whether average outcomes differ by gender, but also whether the instructional conditions that support growth operate similarly for women and men. The gender-specific predictor patterns observed here underscore the value of designing supports that are robust to differing entry points in confidence and prior preparation.

Additional patterns highlight the complexity of students' affective experiences. Men who found the course less challenging reported greater gains in scientific thinking and positive attitudes, while increased nervousness about the course predicted stronger interest and intention to use statistics in the future. This echoes findings from Xu et al. (2021), who observed that students with lower perceived mathematical ability made similar cognitive gains as their higher-confidence peers, even though initial perceptions of ability persisted.

Finally, these findings contribute to ongoing discussions about gender disparities in research and STEM by demonstrating that an applied, data-and-computing-driven, project-based approach can support equitable learning experiences within an introductory statistics course. Women remain underrepresented in research and STEM both in Africa and globally (UNESCO Institute for Statistics, 2022), yet the present findings suggest that instructional approaches such as PDS can support engagement and learning-related gains across gender. The curriculum's emphasis on real-world, contextually relevant data (Hamouda et al., 2025), collaborative learning (Kalaian & Kasim, 2014), and personal choice with individualized support (Chernikova et al., 2025) appears especially effective in cultivating an inclusive environment. By aligning learning with students' own interests and contexts, the PDS model not only builds technical competence but also promotes identification with the role of "scientist," thereby supporting more diverse pathways into the research enterprise.

A limitation of the present study, however, is the absence of a comparison group using an alternative instructional approach, which limits causal interpretation and prevents direct comparison to other pedagogical models. This study was designed as an implementation and feasibility evaluation rather than a controlled instructional trial, with the goal of understanding how the pedagogical model functions in a new educational and cultural context. Evaluating the curriculum in an intact classroom setting allows examination of authentic student engagement and equity-related outcomes, but does not permit causal inference. Future research employing quasi-experimental or experimental designs would be valuable for establishing comparative effectiveness.

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APPENDIX A: CODEBOOKS & RESEARCH QUESTIONS (PROJECT ASSIGNMENT 1)

The purpose of this assignment is to:

1. Read an example of survey research conducted using secondary data.
2. Begin thinking about possible research questions for your individual research project in statistics.

Assignment preparation:

Download the following article from the Week 3 module on Canvas:

Cheeseman, N. (2014). *Does the African middle class defend democracy? Evidence from Kenya*. Retrieved from WIDER working paper website: https://www.econstor.eu/handle/10419/102988

Assignment steps:

1. Read Cheeseman (2014) following these guidelines for reading scientific research papers:
    - ***First, read the introduction*** (skip the abstract – typically you would read the abstract to decide whether to continue reading the whole article). From the introduction you should be able to determine the population of interest, the authors' motivation for doing the study, the hypothesis, explanatory and response variables, and key findings.
    - ***Second, read the Discussion & Conclusion sections.*** These sections will detail the key findings and implications of the study.
    - ***Third, skim the Methods section.*** Determine the sampling approach, sample size, and how the explanatory and response variables were measured.
    - ***Fourth, skim the Results sections.*** Pay attention to tables and graphs, they are a good way to get an overview of the results.
    - ***Lastly, return to the methods and results sections if more detailed information is needed.***
2. Answer each question below with one or two complete sentences:
    a. Why is the quote "No bourgeoisie, no democracy" relevant to this research?
    b. What is the population of interest?
    c. What is the hypothesis the author is testing?
    d. What is the explanatory variable and how is it measured?
    e. What is the response variable and how is it measured?
    f. What is the sample size?
    g. Which round of the Afrobarometer study was used and when was the data collected?
    h. Summarize the key findings of the study.
    i. This study was conducted using Afrobarometer data from Kenya. Do you think the findings would be similar or different if the study used data from Ghana or from your home country?
3. Your instructor will share with you several datasets you can use for your research project in statistics (or you may source your own dataset with approval). Choose one of the datasets that piques your interest, read information about the dataset online, and ***write one to two paragraphs*** summarizing what you have learned. Include information about how long the research has been ongoing, the objectives, population of interest, countries involved, funders, sampling and data collection methods, sample size, topic focus, etc.
4. Download (from Canvas) the codebook for the dataset you chose to review in question 3. Scan through the codebook from beginning to end. ***List three topics*** covered in the survey that you might find interesting for a research project in statistics. For example, if there are several

questions in the codebook about contraception, then contraception is a topic covered in the survey, and therefore, could be a topic for your research. Only topics included in one of the codebooks shared by your instructor can be selected for your research project.

5. One of the simplest research questions that can be asked is whether two variables are associated. For example:
    - Is medical treatment seeking associated with socio-economic status?
    - Is water fluorination associated with number of cavities during dentist visits?
    - Is alcohol use in adolescence associated with diagnosed mental health conditions in young adulthood?
    - Is the age at which adolescents become sexually active associated with the choice of contraception?

    Based on the topics you identified in question 4, ***write three possible associations*** you could test using the variables in the codebook. Use the template below.

    IMPORTANT: Each association MUST be between two variables in the codebook! If one of the variables in the association is not in the codebook than the relationship cannot be tested!

    a. "Is ______________________________ associated with _____________________?"
    b. "Is ______________________________ associated with _____________________?"
    c. "Is ______________________________ associated with _____________________?"

<u>ASSIGNMENT SUBMISSION</u>: Submit answers to questions 3, 4 and 5 only. Upload to Canvas by 11:59 pm on Tuesday, 22nd September.

APPENDIX B: FINAL POSTER GRADING RUBRIC

Name: ________________________________

	Poster Components	**Total Points**	**Score**	**Comments**
1	**Introduction**			
	Title, intro (interest, relevance), literature (3 current relevant peer reviewed sources, clearly summarized, APA intext format), research questions (wording, accuracy, researchable, complexity, originality)	15		
2	**Methods**			
	Description of sample (source, year, age/gender, subset, size), measures (survey question and response categories, aggregate or collapsed variables), and hypotheses	15		
3	**Graphs**			
	Titles, axis labels, category names (min 2, visually appealing, clear and accurate, interpretable)	20		
4	**Results**			
	Summary statistics (category proportions and/or category means and standard deviations), bivariate results (test statistic, df, p-values, r, r-squared), conclusion in context (following statistical conventions), post-hoc results if needed, slope if needed, effect size noted (practical significance)	20		
5	**Discussion**			
	Discussion and recommendations are relevant and drawn from the outcomes of the study, connect to literature, speculate about causes and/or offer policy recommendations and/or recommendations for further research	15		
6	**References**			
	3 to 5 APA formatted references (minimum 3 peer reviewed journal articles), including reference for the secondary data	10		
7	**Participation in the poster session**			
	Relevant and useful comments and ratings on at least 3 poster presentations by colleagues	5		
	TOTAL	**100**		