Journal of Advanced Sciences and Mathematics Education
Volume 5, Issue 2, 239 - 252
e_ISSN: 2798-1606
DOI: 10.58524/jasme.v5i1.709

Exploring first-year students' reasoning gaps in bivariate analysis: A case study from a resource-limited higher education context

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Article Info

Article history:

Received: April 25, 2025
Revised: July 27, 2025
Accepted: Aug 08, 2025

Keywords:

Bivariate analysis;
Conceptual errors;
Statistical education;
Student difficulties.

Abstract

Background: Many students struggle with bivariate analysis, especially where digital tools are lacking and manual methods dominate learning.
Aim: This study seeks to uncover the types of conceptual misunderstandings and procedural errors that first-year undergraduate students encounter when solving problems related to correlation and regression. It also aims to explore the underlying factors contributing to these difficulties.
Method: A qualitative analysis was conducted using examination scripts from 120 first-year students enrolled in a Descriptive Statistics and Probability module at a South African open distance learning university. The students' responses to questions on linear correlation, regression fitting, and prediction were examined through a combination of descriptive statistics and deductive content analysis.
Results: The analysis revealed a wide range of misconceptions. While 80% of students could correctly identify variables, only 41.7% computed the correlation coefficient accurately, 36.7% fitted the regression line correctly, and 33.3% predicted y-values properly. Frequent errors included misusing formulas, confusing statistical terms, and failing to check the plausibility of results. Manual methods, in particular, increased the risk of computational and interpretative mistakes.
Conclusion: The findings point to substantial gaps in both conceptual understanding and procedural fluency among novice statistics students. To support better learning outcomes, educators should prioritize teaching strategies that integrate conceptual clarity, multiple solution paths, and routine validation practices, especially in contexts where digital tools are not widely available.

To cite this article: Makwakwa, E. G. (2025). Exploring first-year students' reasoning gaps in bivariate analysis: A case study from a resource-limited higher education context. *Journal of Advanced Sciences and Mathematics Education, 5*(2), 239-252.

INTRODUCTION

Understanding how students engage with foundational statistical concepts is increasingly important in today's data-driven world. One area that remains particularly challenging for beginners is bivariate analysis, which involves examining the relationship between two quantitative variables. Although this topic is fundamental in introductory statistics courses, many students struggle to apply it correctly in practical situations (Schwab-McCoy et al. 2021). The challenges are not limited to computational mistakes but include confusion about which variables are dependent or independent, how to calculate correlation coefficients, and how to interpret regression equations (Chicco et al. 2021). These difficulties point to deeper reasoning issues that are not always addressed through standard teaching approaches. Particularly in resource-constrained educational environments, the absence of technological tools often forces students to rely on manual methods, which may further obscure their conceptual understanding (Alrawashdeh, 2023). While these manual techniques aim to reinforce mathematical thinking, they sometimes introduce barriers to insight. Therefore, it becomes urgent to investigate how student reason through bivariate problems without the aid of digital computation.

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In settings where access to statistical software is limited, students often face additional hurdles in developing their skills. Open distance learning (ODL) institutions, for example, commonly assess students using paper-based exams and non-programmable calculators (Childress et al., 2023). This method is practical given infrastructural limitations, but it may unintentionally narrow the focus of learning to formula memorization and arithmetic execution. As a result, students might perform calculations without understanding the logic behind them, and this weakens their ability to interpret the meaning of their answers (Braithwaite & Sprague, 2021). Misinterpretation of trends, failure to validate results, and inconsistent reasoning are often seen in student responses under such conditions. These patterns reveal the need for deeper pedagogical inquiry. While some learners may enter university with prior exposure to statistics, others may lack any structured background, which further complicates teaching (Lin & Chen, 2024). This variability in readiness raises important questions about the effectiveness of one-size-fits-all instruction. Without targeted support, early difficulties can snowball into long-term gaps in statistical literacy.

The urgency of this study is also reinforced by broader curricular shifts intended to strengthen data literacy from an early age. In countries like South Africa, for example, the integration of statistical topics into the high school curriculum has been an evolving priority since the late 1990s (Sahlberg, 2023). Despite this, large-scale assessments such as TIMSS and SAQMEC continue to show that students enter tertiary education with limited ability to interpret and apply statistical concepts. While high school curricula might introduce terms like "correlation" or "regression," they often do so in a fragmented way, disconnected from real-world applications. As a result, many students arrive at university unprepared for tasks that demand both numerical skill and conceptual insight. This disconnect between secondary and tertiary education needs to be better understood if we hope to improve student outcomes (Keane et al., 2023) . By identifying the exact points where students falter, educators can better align instructional strategies with learners' needs. Research that bridges this transition is crucial to closing persistent achievement gaps. Bivariate analysis, as one of the earliest multivariable skills introduced, provides a timely and revealing context for such investigation (Johnson IV et al., 2021).

What makes this issue more pressing is the assumption often held by instructors that students have already mastered foundational topics. In reality, many first-year students may remember procedural steps but lack a grasp of their purpose (Cameron & Rideout, 2022). They may plug values into formulas correctly, but without knowing why those formulas are used or how the numbers relate to data behavior. For example, a student might calculate a regression coefficient without realizing it reflects the slope of a best-fit line (Bjärehed et al., 2021). Or they may compute a correlation value without checking whether the result makes sense given the scatterplot. These types of errors are not rare, they appear across many exam scripts and reveal a shared pattern of superficial learning. If left unaddressed, such shallow understanding can hinder students from progressing to more complex statistical methods. This situation underscores the need to study not only what students get wrong, but how they are thinking when they do. Doing so allows educators to move beyond correction and toward constructive redesign of instruction (Jahnke et al., 2022).

Although some scholars have discussed the use of active learning and technology in improving statistics education (Børte et al., 2023), less is known about how students perform under traditional, manual conditions. Most of the existing research centers on teaching strategies or software-based learning environments, which do not always reflect the reality in under-resourced institutions. There is limited empirical analysis of students' hand-written work, especially in high-stakes assessments where no software tools are allowed (Lynch, 2022). This gap is significant because manual responses often expose reasoning in ways that digital tools conceal. When students write out every step, their assumptions, habits, and misconceptions become more visible. Analyzing such responses provides a window into their mental models and reveals how they are interpreting questions. It also highlights which concepts are robustly understood and which remain fragile. This kind of close, qualitative examination is essential to designing teaching that is both accessible and effective.

Beyond conceptual misunderstandings, procedural breakdowns are also common in bivariate problem solving. For instance, students may confuse the slope with the intercept, reverse the variables when plugging into regression equations, or fail to use the correct formula for correlation (Wysocki et al., 2022). These are not simply errors in math, they indicate breakdowns in comprehension that require targeted intervention. Compounding the issue, students rarely verify their answers, even when they seem unreasonable (Shoufan, 2023). A negative correlation value in a clearly positive dataset may go unquestioned, simply because the student followed the steps. Teaching students how to critically evaluate their results, not just how to produce them, must be part of statistics education. This calls for an instructional shift from product to process, where the emphasis is placed on reasoning, not just result. In low-tech contexts, this shift can still happen through paper-based strategies that promote reflection. But to do that, we must first understand where students are going wrong and why.

This study is particularly timely because it addresses both cognitive and contextual factors affecting student learning. The setting, a distance learning university that conducts manual exams, offers a clear view of how students operate without technological assistance (Lee & Fanguy, 2022). By examining actual student responses to key bivariate tasks, the research provides evidence on how learners approach problems when only their own reasoning is available. This kind of data is rare and valuable, especially in global conversations around equitable education. It highlights the realities faced by students in environments where resources are limited but expectations remain high (Rahiem, 2021). It also challenges assumptions that students who perform poorly are simply unmotivated or careless. Often, they are doing the best they can with the tools and knowledge they have. Understanding this can help shift the narrative from deficit to support. It also offers concrete guidance for educators, curriculum developers, and policymakers.

Ultimately, the need for this study lies in its potential to improve teaching and learning in meaningful ways (Onu et al., 2024). By identifying the patterns of misunderstanding in bivariate analysis, educators can redesign instruction to prevent these errors rather than remediate them. Strategies such as multiple-solution approaches, explicit teaching of validation, and connection between computation and interpretation can all stem from these insights. Ezeamuzie et al. (2022) Additionally, this research contributes to a larger body of work calling for educational equity—not only in access to resources but also in access to understanding. When students learn how to reason with data, they are better equipped for both academic success and informed citizenship. But that reasoning must be nurtured, not assumed. This study serves as a step toward that goal, focusing on the intersection of content, context, and cognition. In doing so, it invites a more human-centered approach to statistics education, one that sees errors not as failures, but as clues to better teaching.

Difficulties in bivariate analysis often stem from students' limited understanding of variable roles, correlation, and regression concepts. Zheng et al. (2025) found that internal factors like self-control and motivation strongly influence success in mathematical reasoning. Similarly, Chang et al. (2025) demonstrated how attention levels correlate with academic performance, suggesting that statistical tasks may overwhelm students lacking focus. In a broader context, Wu et al. (2024) showed how reasoning gaps affect data interpretation, which mirrors challenges seen in statistical learning. From a modeling perspective, Li (2024) introduced decision-making frameworks that highlight the importance of evaluating patterns critically, an ability many students have yet to develop. The digital divide adds complexity, Gutiérrez-Marín et al. (2025) noted how restricted access to technology can widen learning gaps in computation-heavy subjects. To address this, Sanusi et al. (2025) emphasized the role of stepwise scaffolding in analytical tasks, while Taoukidou et al. (2025) recommended exposing learners to multiple modeling strategies. Meanwhile, Frayon et al. (2024) linked academic outcomes to well-being, reminding us that learning contexts matter. Dionne et al. (2024) pointed to the need for institutional support in shaping professional development, which is essential for effective statistics instruction. Showcased the depth of insight achievable through bivariate modeling, underscoring what students might miss without guided reasoning.

Understanding how students engage with bivariate analysis is becoming increasingly important, especially as data literacy grows in relevance across disciplines. Yet, for many first-year students, topics like correlation and regression remain difficult to master, more so in settings where digital resources are minimal. In open distance learning environments, for example, students often rely on manual computation using basic calculators rather than statistical software. While this approach is practical in low-resource settings, it also presents a challenge: students are required to solve multi-step problems with limited support. Existing research has largely focused on digital learning interventions or conceptual teaching strategies, often without exploring how students actually solve statistical problems by hand. This study positions itself within that space, emphasizing the need to better understand student thinking in realistic, low-tech conditions. Investigating how students reason through bivariate tasks manually offers a more grounded perspective on where and why misunderstandings occur. Such understanding is crucial if we are to develop teaching strategies that are not just theoretically sound but practically responsive to students' realities.

Although the field of statistics education has grown, there is still a lack of detailed inquiry into how students handle bivariate analysis in traditional, paper-based assessments. Much of the existing literature explores conceptual difficulties in general or emphasizes the benefits of technology-enhanced learning. However, few studies have taken a close look at students' handwritten responses in exam conditions, particularly in institutions where software use is either restricted or entirely absent. There is also limited work documenting the specific kinds of reasoning errors students make when asked to compute correlation coefficients, fit regression lines, or interpret prediction results. Additionally, how these errors relate to broader contextual factors, such as curriculum design, assessment format, and prior exposure to statistical thinking, is still not well understood. Without addressing this gap, it remains difficult to design learning interventions that meet students where they are, especially in under-resourced academic contexts.

This study was designed to explore the types of difficulties first-year undergraduate students face when working with bivariate analysis problems in a setting that emphasizes manual calculation. Conducted at a South African open distance learning university, the research draws on students' actual exam responses to tasks involving correlation, regression fitting, and prediction. The aim is to examine the patterns of error and misunderstanding that arise when students are required to solve these problems without the help of statistical software. By doing so, the study hopes to provide insights that can inform more effective instructional practices and assessment strategies. In addition, the findings will help highlight the importance of integrating both conceptual clarity and procedural fluency into the teaching of statistics. Ultimately, this research contributes to the wider effort of improving statistical literacy among university students—particularly those learning under constraints that are too often overlooked in educational policy and practice.

METHOD

Research Design

This study adopted a qualitative approach utilizing secondary data to explore the misconceptions students exhibit when solving bivariate analysis problems. Rather than collecting new data, the researcher analyzed actual examination scripts, allowing for a realistic view of how students respond to statistical tasks under formal assessment conditions. This design enabled the investigation of not only the answers provided, but also the reasoning patterns and procedural errors embedded within those answers. Conducted within an open distance learning context, the study emphasized the role of manual computation in shaping student understanding. Ethical clearance was obtained through institutional procedures, and only the scripts of students who gave informed consent were included. The qualitative orientation allowed the researcher to focus on error patterns, while the secondary data aspect ensured that the authenticity of student performance was preserved. The steps followed in the research process are visually summarized in the flowchart below.

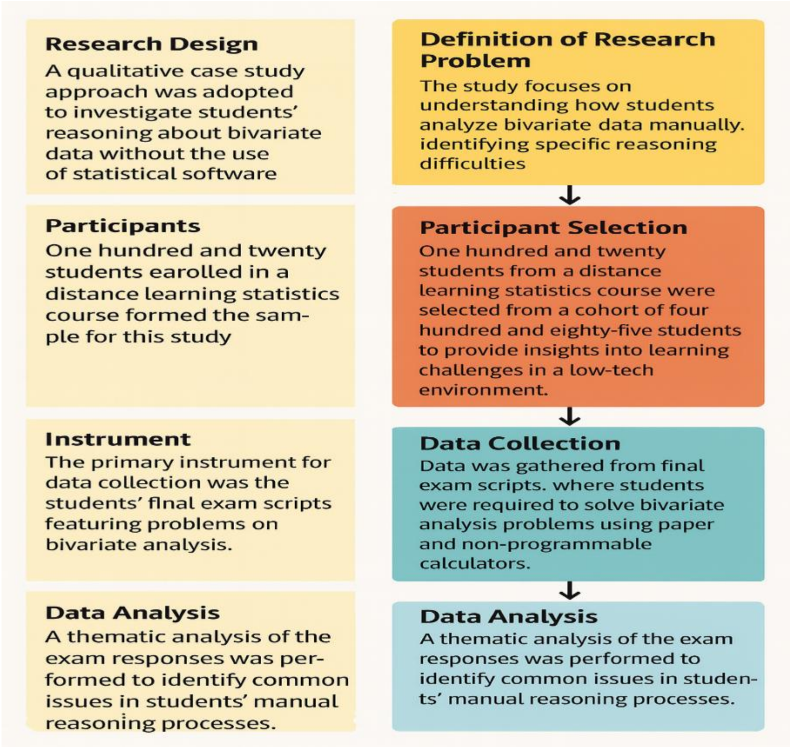

Figure 1. Visual Representation of Research Stages

As shown in Figure 1, the research began with the identification and selection of participants from an existing exam cohort. Once consent was obtained, examination scripts were reviewed to select responses that addressed questions related to bivariate analysis. These responses were then organized and analyzed in two stages: first through a descriptive classification (correct, incorrect, or blank), and then through content analysis to identify common patterns of misconceptions. The flow ensured that the research remained systematic and closely aligned with the study's goals of understanding how students reason through statistical problems manually.

Participants

The study involved 120 first-year undergraduate students enrolled in a Descriptive Statistics and Probability module at a South African open distance learning university. These students were selected from a larger cohort of 485 enrolled in the same module during the semester of study. Their inclusion was based on voluntary consent to allow their written exam scripts to be used for research purposes. The sample included 45 female and 75 male students, with diverse academic backgrounds. Most participants had completed their secondary education in South Africa, while a smaller number had obtained equivalent qualifications from other countries. This diversity added nuance to the analysis, enabling the researcher to capture a broad range of reasoning styles and misconceptions. Participation in the study did not affect academic outcomes, and confidentiality was maintained throughout.

Instruments

The main data source for this study consisted of students' handwritten examination scripts from a final venue-based assessment. These exams were completed using traditional paper-and-pencil methods, under standard university testing conditions. Students were allowed to use non-programmable scientific calculators and were provided with standard formula sheets. The exam itself was developed and moderated by course instructors and reviewed by institutional quality assurance staff to ensure alignment with the intended learning outcomes. From the complete set of examination questions, the researcher selected three that specifically focused on bivariate analysis. One question required students to compute the linear correlation coefficient using summary statistics. Another asked student to identify which variables were dependent and independent in a given context. A third question required the construction of a regression equation using the least squares method, followed by a prediction task based on that equation. These items were chosen because they required both computational accuracy and conceptual understanding, making them well-suited for analyzing students' reasoning under manual conditions.

Data Analysis

Data analysis was conducted in two phases to capture both the quantitative and qualitative dimensions of student performance. In the first phase, student responses were categorized into three groups: correct, incorrect, and blank. This categorization provided a snapshot of proficiency levels and highlighted which types of tasks were most problematic for students. Table 1 presents the outcome of this classification.

Table 1. Students' Proficiency in Bivariate Analysis Tasks

Question	Correct	Incorrect	Blank	% Proficient	% Non-Proficient
4a (Correlation Coefficient)	50	59	11	41.7%	58.3%
4b(i) (Identify Variables)	96	19	5	80.0%	20.0%
4b(ii) (Fit Regression Line)	44	59	17	36.7%	63.3%
4c (Prediction Using Regression)	40	49	31	33.3%	66.7%

In the second phase, a deductive content analysis was applied to examine the nature of students' reasoning in the incorrect or incomplete responses. This phase focused on identifying conceptual misunderstandings—such as confusing slope with intercept or using the wrong variables—as well as procedural errors like formula misapplication or failure to verify results. Each error pattern was coded and grouped under thematic categories. Representative student excerpts were used to illustrate key points, supporting the interpretation with concrete examples. This dual approach allowed the research to move beyond surface-level outcomes and into a deeper understanding of student thinking.

RESULTS AND DISCUSSION

Results

This study examined the written responses of 120 students to four key questions on bivariate analysis. Each question assessed a specific concept: correlation, identification of variable roles, construction of regression equations, and prediction using a regression model. Across all questions, a clear pattern emerged, students tended to perform well on tasks requiring identification but faced significant challenges in computational and interpretive problems. The most successful performance was observed in identifying independent and dependent variables, with 80% of students answering correctly. However, only about one-third of the students managed to solve the regression and prediction questions accurately. This gap between recognition and application reflects a deeper issue in how students internalize statistical concepts.

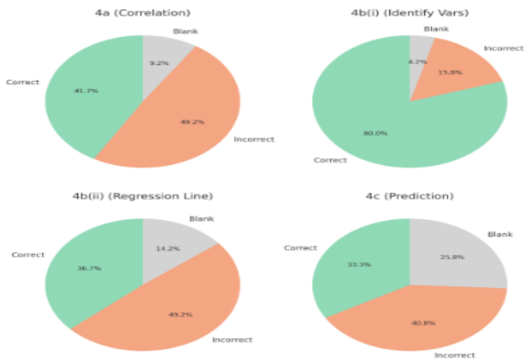

Figure 2. Distribution of Student Responses per Question in Bivariate Analysis Tasks

A set of pie charts, illustrates the proportion of correct, incorrect, and blank responses for each question. It reveals that while Question 4b(i) had the highest rate of correct answers, the final question, asking for prediction using a regression model, had the largest share of unanswered responses.

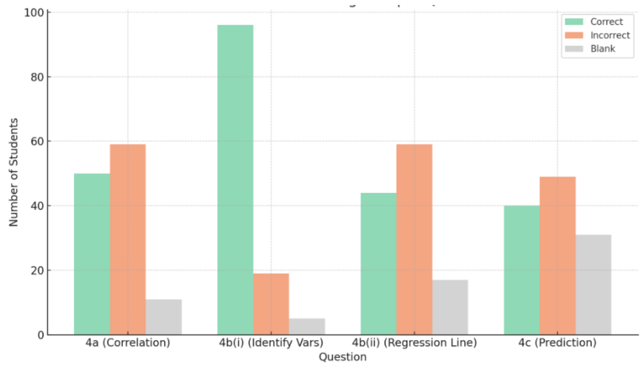

Figure 3. Students Answer Categories per Question

A bar chart comparing the number of correct, incorrect, and blank responses per question, reinforces this point and makes the drop in performance across the questions more apparent.

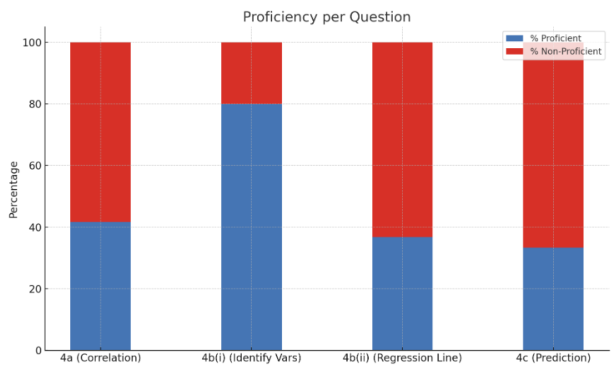

Figure 4. Proficiency per Question

The results are converted into percentage form, showing how many students were proficient versus non-proficient in each task. The visual contrast between the high success rate in variable identification and the much lower rates in regression and prediction emphasizes the shift in cognitive demand.

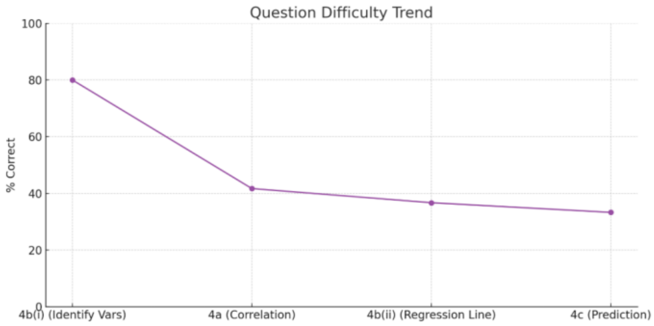

Figure 5. Question Difficulty Trend

Offers a line chart representing the relative difficulty of the tasks. The sequence follows a clear downward trajectory, starting from the highest-scoring task (4b(i)) to the most difficult (4c), suggesting that complexity played a key role in student performance. Looking deeper into the responses, many students who answered incorrectly on Question 4a showed confusion in how to structure the correlation formula. Some neglected to include key elements such as the square root, while others substituted values in the wrong places. These types of errors suggest that students may have memorized the formula but did not fully understand how or why it works.

In Question 4b(ii), which required construction of a regression equation, common mistakes included reversing the roles of variables, miscalculating slope or intercept, or failing to complete the formula altogether. Even among those who made partial progress, many were unable to write the final equation correctly. Interestingly, some errors were consistent across multiple scripts, indicating a shared misunderstanding rather than isolated mistakes. As for Question 4c, the challenge was more evident. Many students either used the wrong numbers or failed to carry out the prediction entirely. Nearly a quarter of them left this question blank, which might signal uncertainty, lack of confidence, or time pressure during the exam. Among those who attempted it, some answers revealed that students had confused the logic of input and output in the regression equation.

Taken together, these findings reflect a broader pattern. Students seem to manage when the task involves recognition or recall but begin to struggle when asked to combine knowledge and execute multi-step procedures. The shift from conceptual familiarity to practical application exposes weaknesses in how well students are internalizing the logic of bivariate relationships. While their errors vary in form, the consistency of these challenges points to a need for better instructional strategies, ones that foster deeper understanding, not just procedural practice.

Discussion

Understanding students' struggles in mastering bivariate analysis is critical, especially when they are required to operate without the aid of technology. The findings of this study showed that while students could easily identify variables, they faced far greater difficulty when asked to calculate correlation coefficients or construct and apply regression models. These patterns reflect a learning gap that is deeper than mere procedural errors. As emphasized by Taoukidou et al. (2025), students often retain superficial knowledge of statistical terminology but lack the cognitive structures needed for application and interpretation. This observation becomes even more important in open distance learning (ODL) contexts, where students rely on self-guided learning and manual computation. The absence of digital tools inadvertently exposes the raw quality of students' reasoning. For educators, this provides a valuable opportunity, not just to correct, but to understand how learners think. Instruction must shift from testing memory to cultivating structured reasoning.

The correlation task in this study exposed more than just computational weakness, it revealed confusion about the nature of statistical relationships. Many students skipped the square root, misidentified variables, or inserted values without verifying the logic behind them. These mistakes are not simply mechanical; they illustrate described as a lack of symbolic fluency, the ability to interpret what formulas mean in real contexts. Relying solely on memorization makes learners vulnerable under pressure, especially in low-tech environments where they cannot double-check their answers. When students fail to grasp what correlation measures, the calculation becomes meaningless. Instructors should consider using examples that connect correlation to intuitive, real-life relationships. Estimating trends from scatterplots before solving, for instance, could promote conceptual anchoring. In time, such practices can shift the focus from formula-following to pattern-recognition. Difficulties escalated in the regression task. Many students either reversed the dependent and independent variables or failed to construct a full regression equation. This is consistent with findings by (Zheng et al., 2025), who noted that when students are not explicitly taught the meaning of regression components, they are unlikely to apply them correctly. The slope and intercept, if taught as mere symbols, lose their explanatory value. Some responses in this study were half correct, indicating that students might know how to begin a solution but not how to complete it. Educators can treat these partial efforts as instructional openings rather than failures. Discussing the logic behind slope, how one variable changes with another, can help solidify understanding. Contextualizing equations with real-life data stories also makes statistical models more relatable. When learners see meaning in math, they engage more deeply.

Prediction proved to be the most difficult task. Not only were answers frequently incorrect, but a large number of students left the question blank. They either lacked confidence in applying the regression model or misunderstood how to plug values into the equation. According to (Ezeamuzie et al., 2022) , the skill of making a prediction requires more than computation, it demands the ability to reason through uncertainty and infer likely outcomes. In this study, most students seemed to approach prediction as a fixed calculation, not as an estimate with assumptions. This rigidity limits their understanding of statistics as a tool for informed decision-making. Teachers can introduce open-ended prediction tasks where multiple answers are acceptable within a logical range. Encouraging students to justify predictions, even without full accuracy, builds confidence and critical reasoning. The goal is not just right answers, but thoughtful ones.

The number of blank responses, especially in the prediction task, may signal more than content gaps—it may reflect affective barriers. Roughly a quarter of students left this section blank, possibly due to anxiety or uncertainty. (Gutiérrez-Marín et al., 2025) suggests that emotional safety plays a significant role in students' willingness to attempt challenging problems. If students feel they cannot succeed, they may choose not to try at all. In distance learning contexts, where feedback is often delayed or impersonal, such feelings can intensify. Educators should normalize struggle as part of learning and reward effort, not just results. Prompts like "Explain what you would do, even if unsure" can foster bravery in problem solving. Students must learn that partial reasoning is still valuable. Cultivating this mindset is essential for long-term resilience in statistical thinking.

Another issue uncovered was the absence of self-checking or validation among most students. Even when answers were clearly illogical, they were submitted without hesitation or review. (Sanusi et al., 2025) has argued that validation (asking whether a result makes sense) is a critical but often neglected skill in mathematics education. This skill is especially important in statistics, where interpretation is key. Teachers must model what it means to pause and question, "Does this answer match what I expect?" Embedding checkpoints in exam questions, such as estimation before computation, could build this habit. In environments without calculators, reasoning becomes the most powerful tool available. Students must be empowered not just to solve, but to reflect. Teaching validation is as important as teaching formulas.

Interestingly, many students gave responses that were partially correct, suggesting the presence of emerging understanding. For example, a student might compute the slope correctly but fail to complete the regression equation. These patterns suggest that the student is reasoning, but incompletely. Rather than labeling such attempts as wrong, teachers should see them as developmental stages. Wu et al. (2024) emphasized that learning progresses through approximations, and recognizing "almost right" can help learners grow. Providing feedback that highlights what was done correctly encourages persistence. Educators should celebrate effort and build on it, especially in paper-based assessments where process matters. Such formative strategies transform exams into diagnostic tools. When used this way, even mistakes have instructional value.

Another consistent pattern was students' reliance on formulaic steps without understanding their meaning. This kind of procedural thinking, where formulas are memorized but disconnected from data behavior, limits transferability. Frayon et al. (2024) found that when students see math as rules rather than relationships, they struggle with complex or unfamiliar problems. This study supports that view. When students cannot connect the slope of a regression line to the idea of rate of change, they may execute steps without knowing what they mean. Instruction must reconnect statistics to reasoning by encouraging interpretation before and after calculation. Asking students to explain what a number tells us "not just how to find it" can foster conceptual depth. Such thinking can be taught and does not require technology. It only requires intent.

Performance differences across students may be linked to varied prior exposure to statistics. Some students may have had access to structured instruction before entering university, while others may be seeing statistical concepts for the first time. This variation challenges one-size-fits-all teaching models. Dionne et al. (2024) advocates for differentiated learning pathways, especially in foundational quantitative subjects. Instructors could offer optional review materials or diagnostic pre-tests to identify who needs reinforcement. Peer tutoring, scaffolded modules, and problem-solving clinics can also narrow readiness gaps. In the context of distance learning, asynchronous resources allow students to review concepts at their own pace. Equity in outcomes begins with equity in opportunity. Providing different entry points for different learners is a mark of inclusive education.

Finally, this study underscores the value of analyzing handwritten responses as a window into student reasoning. Unlike digital platforms, manual work reveals not only the final answer, but the cognitive path that led to it. Li (2024) emphasizes that written responses allow educators to spot misconceptions early, adjust instruction, and design more responsive assessments. In this research, we saw that what students wrote (errors and all) held rich insight into their understanding. Instead of discarding flawed answers, teachers can mine them for instructional gold. Recognizing common misconceptions enables proactive teaching. In ODL environments, where face-to-face interaction is limited, written responses become crucial data. They help us understand not just what students know, but how they think.

Implications

This study brings to light critical insights about how students interact with foundational statistical concepts in low-resource educational contexts. One of the key implications is the realization that successful performance in statistics is not merely a matter of memorizing formulas or completing calculations. Instead, deep conceptual understanding is essential, especially when learners are expected to navigate problems without the support of technological tools. The prevalence of reasoning errors in tasks such as correlation interpretation and regression modeling suggests that many students operate at a procedural level, lacking awareness of the underlying statistical logic. This has pedagogical consequences. Educators must look beyond traditional instruction and ask how students make sense of what they're doing. By identifying where students go wrong, such as confusing slope and intercept or failing to validate results, teachers can better tailor their interventions to promote understanding rather than repetition. Furthermore, in distance learning environments where face-to-face clarification is limited, course designers should incorporate reflective activities, guided practice tasks, and targeted error analysis into instructional materials. This could foster deeper engagement with content and reduce misconceptions. The study also emphasizes that students' written work, even when incorrect, is a rich resource for curriculum improvement. Designing assessments that capture reasoning, not just results, can reshape how learning is measured and supported in open learning environments.

Limitations

Despite its relevance, this study is bounded by several limitations that must be acknowledged to contextualize its findings. Firstly, the research relied solely on written responses from a single cohort of students within one university. While the data offer meaningful insights, the narrow sampling frame limits the generalizability of the conclusions to broader populations or educational systems. Diverse learning cultures, technological access, and prior exposure to statistical content could yield different patterns of misunderstanding elsewhere. In addition, the analysis did not include any interviews, observations, or self-reported data that might illuminate students' thought processes, emotional reactions, or confidence levels while completing the tasks. These affective and metacognitive dimensions are crucial in understanding how learners approach complex problems but were inaccessible through the static format of exam scripts. The scoring framework—categorizing responses as correct, incorrect, or blank—while useful for clarity, may obscure nuanced thinking. Some incorrect answers may reflect promising reasoning interrupted by minor missteps, and these deserve more detailed investigation than binary coding allows. Moreover, the exclusive focus on bivariate analysis, while intentional, does not capture the full range of statistical competencies required in a complete course or curriculum. Therefore, conclusions should be understood as specific to this content domain rather than generalizable to all statistical learning.

Suggestions

Future inquiries into students' statistical reasoning would benefit from methodological expansion. Including interviews, verbal protocols, or process-tracing methods such as think-alouds would add a qualitative richness to the data, allowing researchers to better understand not only what mistakes students make, but why they make them. These techniques would help uncover reasoning strategies, conceptual confusion, or even test anxiety that might not appear in written answers. Extending the sample to include students from multiple institutions, including both high-tech and low-tech learning environments, would also help clarify whether the observed misconceptions are context-dependent or broadly systemic. On the instructional side, there is a need to reconsider how we scaffold learning in statistical modules. Rather than focusing exclusively on computational accuracy, instruction should foreground interpretation, estimation, and validation. Embedding prompts that ask students to justify their choices or reflect on the plausibility of their answers could help develop the habits of mind needed for statistical thinking. Incorporating low-cost diagnostic tools such as error-spotting activities, structured group discussions, or comparative solution tasks can strengthen students' conceptual grasp, even in settings with minimal digital infrastructure. Policy-wise, education leaders must support initiatives that prioritize deep learning and conceptual clarity in statistics, especially in institutions serving remote or under-resourced populations. This may involve training lecturers in evidence-based teaching practices, redesigning assessment formats to emphasize reasoning, or investing in resource development tailored for low-tech environments. Ultimately, addressing the gap between procedural execution and conceptual understanding is not only a pedagogical challenge but also a matter of educational equity.

CONCLUSION

This study revealed that many students, particularly in low-tech learning environments, face significant challenges when dealing with bivariate analysis problems, not because they lack exposure to formulas, but because they struggle with the reasoning required to apply them meaningfully. While identifying variables appeared relatively manageable, tasks involving correlation, regression, and prediction exposed deeper conceptual gaps and recurring misconceptions. These findings suggest that students often rely on procedural memory without truly understanding the relationships behind the data, which can hinder their development of statistical thinking. The insights gained from students' written responses underscore the importance of instructional strategies that go beyond accuracy and encourage critical reflection and validation. In resource-limited educational contexts, such as distance learning programs, it becomes even more crucial to design assessments and teaching practices that foster conceptual clarity through accessible and reflective methods. Rather than treating mistakes as final outcomes, educators should view them as entry points for learning, using them to inform better teaching and support meaningful progress in statistical literacy.

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