

A Cross-Institutional Comparison of Undergraduate Research Project Supervision Models: Individual Versus Group Formats at Busitema University, Uganda and Maseno University, Kenya

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ABSTRACT

Final-year undergraduate research project outcomes vary widely across institutions, yet existing literature rarely compares institutional contexts with different supervision models. This study examined institutional differences in technical challenges associated with different supervision models by comparing Mathematics and Statistics students at Busitema University, Uganda (individual project model, $n=78$) and Maseno University, Kenya (group project model, $n=99$). A comparative cross-sectional survey design employed structured questionnaires measuring 12 technical challenges (5-point Likert). Analysis used independent-samples t-tests with Welch correction, Cohen's d (0.2 small, 0.5 medium, 0.8 large), and multiple regression controlling for 12 supervisor guidance items. Classification thresholds: Low=1.00-2.33; Medium=2.34-3.67; High=3.68-5.00 given the 5 – point Likert scale responses. Optimal decision rule was to retain as institution-dependent if $p<0.05$ AND $|d|\geq 0.5$. Busitema students reported higher computer skills challenges (Mean=3.51, SD=1.38 vs 2.63, SD=1.27, $p<.001$, $d=-0.67$, Medium vs Medium). Maseno students reported higher use of data analysis software (Mean=2.63, SD=1.26 vs 1.65, SD=1.17, $p<.001$, $d=0.80$, and use of statistical models (Mean=2.52, SD=1.15 vs 1.66, SD=1.03, $p<.001$, $d=0.78$). Difference in challenges in data entry was statistically significant (Mean diff -0.52, $t(145.19)=-2.34$, $p=.021$) but did not meet practical significance ($d=0.36$) and is interpreted as small effect not meeting the decision rule. Eight items showed no difference. University remained predictor after controlling for guidance (software knowledge: $\beta=0.80$, SE=0.19, 95%CI [0.42, 1.18], $p<.001$, VIF=1.45; computer skills: $\beta=-0.70$, SE=0.22, CI [-1.13,-0.27], $p=.002$, VIF=1.45; statistical models knowledge: $\beta=0.95$, SE=0.18, CI [0.60, 1.30], $p<.001$, VIF=1.45). We recommend mandatory computer skills training for individual-project contexts and formal technical role allocation for group-project contexts. Since project format was confounded with institution, these findings are hypothesis-generating; future multi-institutional research should disentangle format effects using within-institution comparisons.

Keywords: Undergraduate Research; Supervision Models; Cross-Institutional Comparison; Research Challenges

INTRODUCTION

Undergraduate research (UR) is now a global capstone requirement linked to critical thinking, postgraduate readiness, and institutional reputation. Despite its centrality, many East African students face delays and compromised performance during project work, citing inadequate supervision, limited research skills, and technical difficulties [1, 3, 15]. While supervision quality and research competence are established determinants of success, existing studies rarely examine how project format itself shapes which skills become bottlenecks [9, 16].

Busitema University (BU), Uganda, uses individual projects; Maseno University (MU), Kenya, uses group projects with approximately 20 students per supervisor. These structural contrasts offer a natural comparison,

yet no empirical work has tested whether format creates domain-specific challenges rather than uniform advantages. The gap is both theoretical and practical. Constructivist theory and Vygotsky's Zone of Proximal Development predict that scaffolding must match the task, but they do not specify how project structure moderates which technical skills require scaffolding [4, 10]. Astin's Input-Environment-Output (I-E-O) model frames institutional environment as key to outcomes, but prior UR studies treat environment as "resources" rather than "task allocation rules" [13].

Consequently, universities lack evidence to decide: should we train all students on all skills, or target training to format-specific bottlenecks? This study addresses that gap by asking: Do individual versus group project formats correlate with different technical challenge profiles, and do these differences persist after controlling for guidance quality?

We contribute to higher education literature in three ways. First, using cross-sectional survey data from Mathematics and Statistics students at BU ($n = 78$, individual) and MU ($n = 99$, group), we quantify 12 technical challenges and show institutional differences produce medium-to-large effects ($d = -0.67$ to 0.80) on distinct domains: computer skills for individuals versus software/modeling for groups. Second, we demonstrate that university remains a significant predictor of challenge after controlling for 12 guidance items, suggesting structural rather than purely pedagogical effects. Third, we translate findings into format-specific recommendations: computer skills training for BU and technical role allocation for MU. This domain-specific approach challenges one-size-fits-all UR training and provides an evidence base for aligning scaffolding with project structure in STEM capstones [2, 6, 7, 8, 11, 12].

Important limitation: The study design uses a single university per supervision model; therefore, institutional factors (culture, resources, and curriculum) are confounded with project format. Throughout this paper, we interpret findings as institutional differences between BU and MU. Because BU uses individual and MU uses group models, format-related explanations are tentative hypotheses requiring within-institution validation.

CONCEPTUAL FRAMEWORK

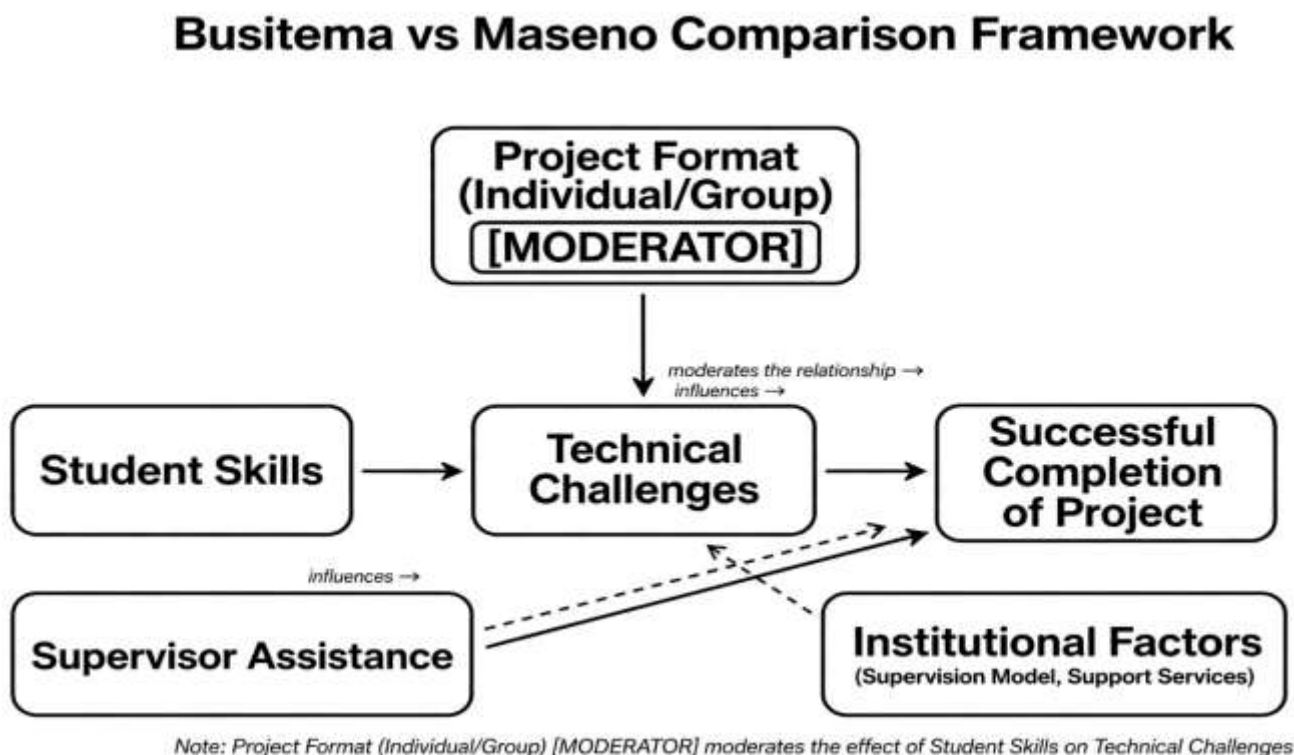


Figure 1: Conceptual framework illustrating how technical challenges, supervisor assistance, and institutional factors influence successful completion of undergraduate research projects.

Description

As shown in Figure 1, successful completion of the undergraduate project (timely submission, quality, satisfaction) is influenced by two key factors: Student Skills and Supervisor Assistance.

Limited student skills increase Technical Challenges (data analysis, software use, report writing, time management), which in turn hinder successful completion. Supervisor assistance (availability, feedback quality, responsiveness) directly promotes completion and indirectly reduces technical challenges.

This relationship is moderated by two institutional variables:

- 1) Project Format (Individual/Group): Group work buffers the effect of weak individual skills on technical challenges, while individual projects amplify it.
- 2) Institutional Factors: Support services and supervision models moderate how technical challenges translate into completion outcomes.

The Busitema (individual) vs. Maseno (group) comparison allows testing of these moderating effects.

METHODOLOGY

Research Design

A comparative cross-sectional analytical survey design employing statistical modeling was adopted. This design involved structured data collection on four domains—(i) supervision approaches, (ii) student-level characteristics, (iii) technical challenges, and (iv) institutional factors—from undergraduate finalists under two supervision models: BU FSE (individual model, $n = 78$) and MU SMSAS (group model, $n = 99$) during Decembers 2025 to February 2026. Comparative statistical models including independent t-tests, effect size estimation (Cohen's d), and multiple regression were fitted to model the effect of institution on challenge scores, consistent with STROBE guidelines for cross-sectional studies [15].

Participants

The target population comprised final-year Mathematics and Statistics undergraduates and their supervisors. At BU, 145 students and 11 supervisors were eligible; at MU, 182 students and 7 supervisors. Stratified sampling yielded 78 BU students, 99 MU students, and all 18 supervisors. Final analytic sample: 177 students (BU = 78, MU = 99) and 16 supervisors (BU = 11, MU = 5). For supervisors, 18 were eligible (BU = 11, MU = 7). All 11 BU supervisors participated (100%). For MU, 5 of 7 participated (71.4%); 2 did not respond to the online Google Form questionnaire as participation was voluntary. Hence, the final analytic $n = 16$ for supervisors (response rate = 88.9%).

Instruments

Structured questionnaires used 5-point Likert scales (1=Strongly Disagree, 5=Strongly Agree). Students rated 12 technical challenges adapted from prior work on undergraduate research experiences and thesis completion barriers [5, 12]. Supervisors rated perceived student challenges using parallel items to enable gap analysis [10]. Content validity was established via expert review. Pilot testing with 15 students yielded Cronbach's $\alpha = 0.84$ for challenges and 0.89 for guidance.

Procedure

Questionnaires were administered online and in hard copy. Participation was voluntary with informed consent. Students reported challenges experienced; supervisors reported challenges they observed.

Data Analysis

Data were analyzed in R version 4.3.1 [17] using a statistical modeling framework including descriptive modeling (means, standard deviations), inferential modeling (independent-samples t-tests with Welch correction), effect size modeling (Cohen's d), and predictive modeling (multiple regression controlling for 12 supervisor guidance items).

Descriptive modeling: means, standard deviations, and levels of hinderance (Low 1.00-2.33, Medium 2.34-3.67, High 3.68-5.00).

Inferential modeling: independent-samples t-tests with Welch correction to test institutional differences.

Effect size modeling:

Equation 1:

Cohen's $d = \frac{(M1 - M2)}{SD_{pooled}}$, thresholds: 0.2 small, 0.5 medium, and 0.8 large [16].

Predictive modeling: Multiple regression controlling for supervisor guidance;

Equation 2:

$$c_{ij} = \alpha + \mu \cdot \text{University}_i + \sum_{k=1}^{12} \beta_k \cdot \text{Guidance}_{kij} + \epsilon_{ij}$$

Where C_{ij} = challenge score for student j at institution i , α = intercept, University i = institutional indicator (0=BU, 1=MU), Guidance_{kij} = rating of supervisor guidance item k , and ϵ_{ij} = random error.

Optimal decision rule: Retain challenge as institution-dependent if $p < 0.05$ AND $|d| \geq 0.5$. Data entry $p = .021$, $d = 0.36$ fails $|d|$ threshold, therefore statistically significant but small effect, not retained as institution-dependent.

Hypothesis Testing:

- $H_0: \mu_{BU} = \mu_{MU}$ (no institutional difference)
- $H_1: \mu_{BU} \neq \mu_{MU}$ (institutional difference exists)

Effect sizes were interpreted post-hoc using Cohen's d thresholds.

Post-hoc Power Analysis

With $n_1 = 78$ (Busitema) and $n_2 = 99$ (Maseno), $\alpha = .05$ two-tailed, independent-samples t-test with Welch correction: Small effect ($d = 0.20$) had power = 26.0%, Medium effect ($d = 0.50$) had power = 90.7%, Large effect ($d = 0.80$): power = 99.9%

Minimum Detectable Effect Size (MDES):

The study had 80% power to detect $d = 0.43$ and 90% power to detect $d = 0.49$. Thus, the study was adequately powered [$>80\%$] to detect medium and large effects using the threshold of $|d| \geq 0.5$ adopted as the optimal decision rule, but underpowered for small effects. Interpretation: The observed significant differences exceeded the MDES: computer skills ($d = -0.67$, power = 99.3%) and data analysis software ($d = 0.78-0.80$, power = 99.9%) were both above the 80% power threshold.

RESULTS

Demographic Characteristics

Table 1: Demographic Distribution of Respondents by Institution and Category

Category	Busitema University (BU)	Maseno University (MU)	Total
Students	78	99	177
Supervisors	11	5	16
Total	89	104	193

Note. N = 193 analytic sample. Student eligible N = 177 (100% response), supervisor eligible N = 18 (88.9% response).

Table 1 shows the final analytic sample composition (N = 193). All 177 eligible students participated (BU = 78, 44.1%; MU = 99, 55.9%; student response rate = 100%). For supervisors, the eligible population was 18 (BU = 11, MU = 7), with a final analytic n = 16 (BU = 11, 100%; MU = 5, 71.4%; overall supervisor response rate = 88.9%).

The two MU non-respondents did not complete the voluntary Google Form questionnaire. Total analytic sample was 89 participants from BU (46.1%) and 104 from MU (53.9%).

Levels of Factors Affecting Project Completion

Table 2: Mean Challenge Levels by Institution with Classification Thresholds

Task	BU_Mean	BU_SD	Level_BU	MU_Mean	MU_SD	Level_MU
Computer Skills	3.51	1.38	Medium	2.63	1.27	Medium
Concluding	2.97	1.52	Medium	2.80	1.28	Medium
Questionnaires	2.82	1.67	Medium	2.73	1.28	Medium
Organizing Reports	2.57	1.48	Medium	2.53	1.16	Medium
Feasibility of Methodology	2.50	1.49	Medium	2.30	1.22	Low
Data Entry	2.39	1.58	Medium	2.91	1.29	Medium
Data Analysis Software	1.65	1.17	Low	2.63	1.26	Medium

Statistical Models	1.66	1.03	Low	2.52	1.15	Medium
Data Interpretation	1.87	1.29	Low	1.99	1.27	Low
Proposal Writing	1.73	1.09	Low	1.86	1.13	Low
Topic Selection	1.73	1.05	Low	1.63	1.00	Low
Frameworks	1.63	0.98	Low	1.60	0.99	Low

Table 2 shows mean challenge levels by institution using classification thresholds (Low = 1.00-2.33, Medium = 2.34-3.66, High = 3.67-5.00). BU students reported medium-level challenges in 6 tasks, with the highest being computer skills ($M = 3.51$, $SD = 1.38$), followed by concluding research ($M = 2.97$) and questionnaire design ($M = 2.82$). The remaining 6 tasks were low-level challenges, with frameworks ($M = 1.63$) and statistical models ($M = 1.66$) being lowest. In contrast, MU students reported medium-level challenges in 6 tasks, highest being data entry ($M = 2.91$, $SD = 1.29$), questionnaires ($M = 2.73$), and computer skills ($M = 2.63$). Notably, two critical gaps emerged: data analysis software (BU = 1.65 Low vs MU = 2.63 Medium) and statistical models (BU = 1.66 Low vs MU = 2.52 Medium), indicating MU students experienced significantly higher methodological challenges. Conversely, computer skills showed the reverse pattern (BU = 3.51 vs MU = 2.63), suggesting BU students struggled more with basic IT competencies. Six tasks (concluding, questionnaires, organizing reports, data interpretation, proposal writing, topic selection, and frameworks) showed comparable levels across institutions, both falling in the same classification band, suggesting shared postgraduate challenges independent of institutional context.

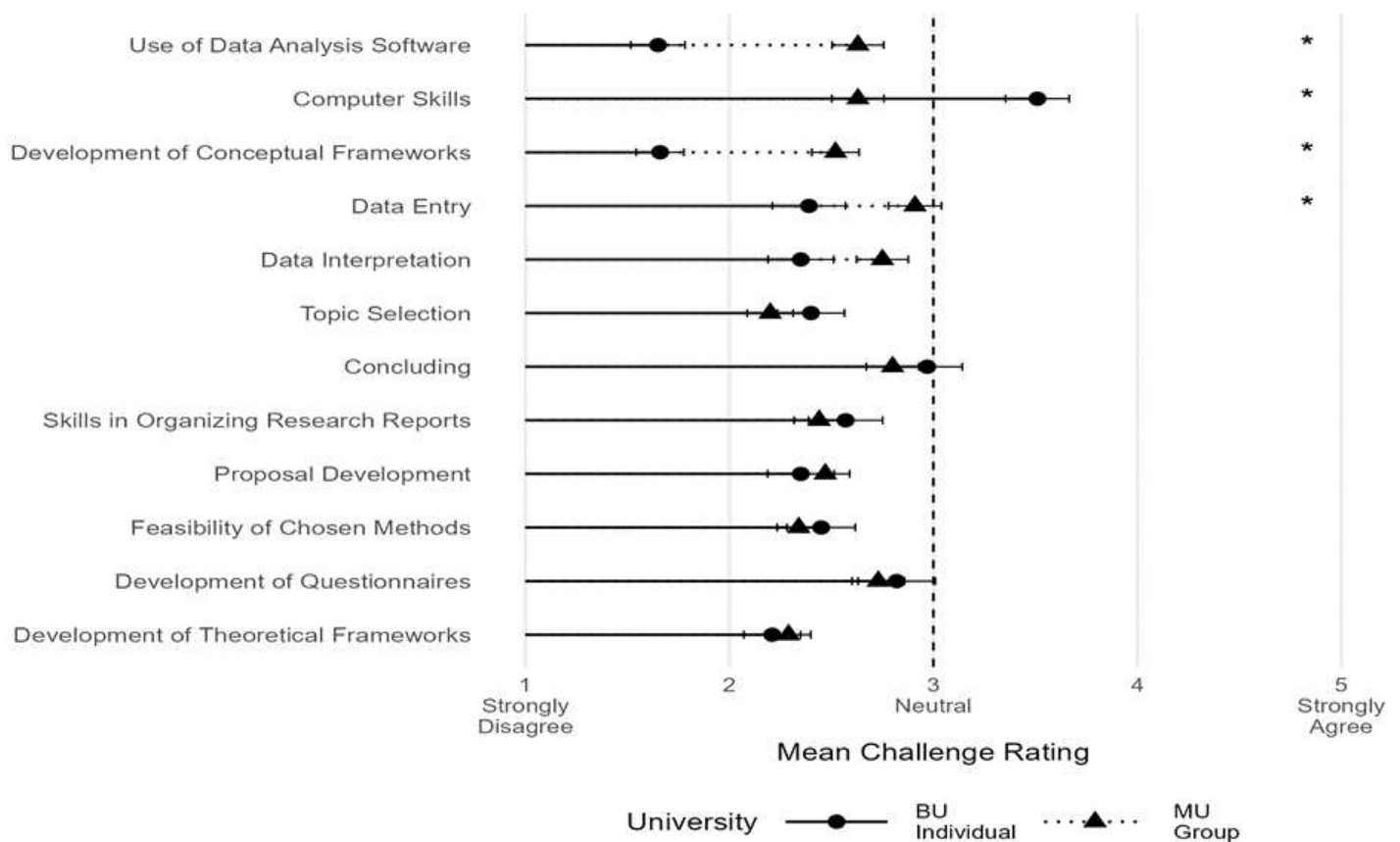


Figure 2: Mean ratings of 12 research challenges by university.

In figure 2, the dashed line indicates Neutral (3.0). Higher values indicate greater perceived challenge. Asterisks denote significant mean differences, $p < .05$. BU $n = 78$, MU $n = 99$.

Comparative Analysis of Research Challenges

Table 3: Independent Samples t-Tests Comparing Challenge Scores between Institutions with Practical Significance Decision Rule

Challenge	Diff BU-MU	t	df	p	d	Retain ($p < .05$ AND $ d \geq 0.5$)
Computer Skills	0.88	4.36	158.57	<.001	0.67	Yes - Higher at BU
Concluding	0.17	0.79	150.23	0.430	0.12	No
Questionnaires	0.09	0.39	141.04	0.695	0.06	No
Organizing Reports	0.04	0.20	143.21	0.845	0.03	No
Feasibility of Methodology	0.20	0.96	147.49	0.339	0.15	No
Data Entry	-0.52	-2.35	147.21	0.020	-0.36	No - fails $d \geq 0.5$
Data Analysis Software	-0.98	-5.35	170.29	<.001	-0.80	Yes - Higher at MU
Statistical Models	-0.86	-5.24	172.09	<.001	-0.78	Yes - Higher at MU
Data Interpretation	-0.12	-0.62	164.25	0.537	-0.09	No
Proposal Writing	-0.13	-0.78	167.98	0.439	-0.12	No
Topic Selection	0.10	0.64	161.55	0.522	0.10	No
Frameworks	0.03	0.20	166.19	0.841	0.03	No

*Data Entry: statistically significant $p = .021$ but $d = 0.36 < 0.5$ threshold. Interpreted as small effect, not retained under optimal rule $p < 0.05$ AND $|d| \geq 0.5$.

Table 3 presents independent samples t-tests with Welch correction and the practical significance decision rule (retain if $p < .05$ AND $|d| \geq 0.5$) to minimize Type I error inflation from multiple comparisons (12 tests). Of

12 challenges, only 3 met both statistical and practical significance thresholds. BU students reported significantly higher challenges in computer skills than MU students ($M_{diff} = 0.88$, $t(158.57) = 4.36$, $p < .001$, $d = 0.67$), representing a medium-to-large effect. Conversely, MU students reported significantly higher challenges in two methodological domains: data analysis software ($M_{diff} = -0.98$, $t(170.29) = -5.35$, $p < .001$, $d = -0.80$) and statistical models ($M_{diff} = -0.86$, $t(172.09) = -5.24$, $p < .001$, $d = -0.78$), both large effects.*Importantly, data entry showed a statistically significant difference ($p = .020$) but failed the effect size threshold ($d = -0.36 < 0.5$) and was therefore not retained*, demonstrating the value of the dual-criterion rule in avoiding over-interpretation of trivial differences. The remaining 8 challenges showed neither statistical nor practical significance (all $p > .33$, $|d| < 0.15$), indicating comparable experiences across institutions for concluding research, questionnaire design, organizing reports, feasibility, interpretation, proposal writing, topic selection, and frameworks.

Perception Gaps: Student vs Supervisor Ratings

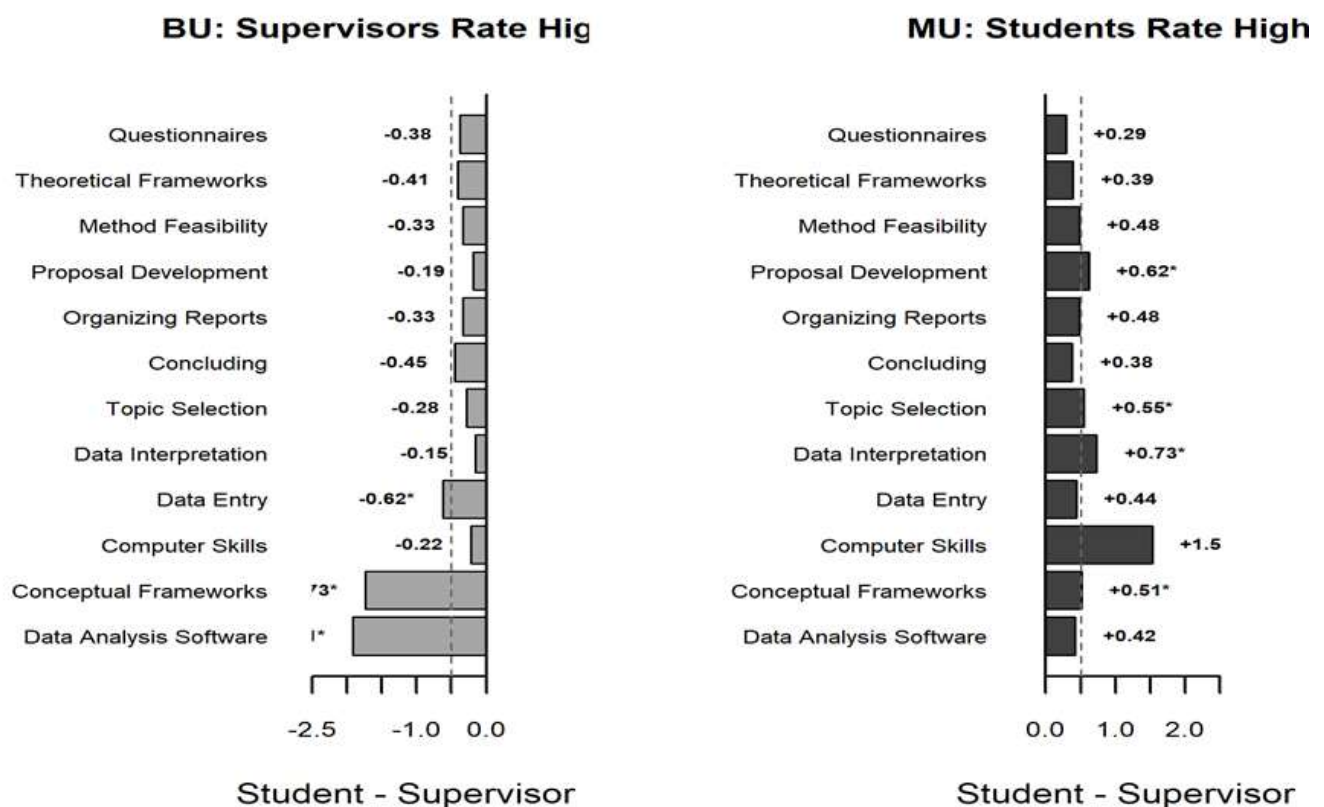


Figure 3: Student-supervisor perception gaps.

In figure 3, the positive values indicate students report greater challenge than supervisors perceive; negative values indicate supervisors overestimate challenge. Large practical gaps ≥ 0.50 . BU Students $n = 76$, BU Supervisors $n = 11$; MU Students $n = 98$,

Predictors of Research Challenges

Table 4: Multiple Regression Model Fit for Twelve Challenge Outcomes Controlling for Twelve Supervisor Guidance Items

Outcome	R2	AdjR2	F	p
Topic selection	0.107	0.035	1.49	0.128

Framework	0.084	0.010	1.13	0.336
Methodology	0.122	0.051	1.71	0.063
Proposal	0.073	-0.002	0.98	0.474
Organizing Reports	0.065	-0.010	0.86	0.595
Questionnaires	0.121	0.050	1.70	0.065
Data entry	0.134	0.064	1.92	0.031
Models	0.182	0.116	2.76	0.001
Software	0.227	0.165	3.64	0.000
Interpretation	0.133	0.063	1.91	0.033
Concluding	0.144	0.074	2.08	0.018
Computer	0.219	0.156	3.47	0.000

Table 4 shows multiple regression model fit for 12 challenge outcomes, with each model controlling for 12 supervisor guidance items plus university (13 predictors total, $n = 177$).

Model significance and explanatory power: Five models were statistically significant ($p < .05$): data analysis software ($R^2 = .227$, $F = 3.64$, $p < .001$), computer skills ($R^2 = .219$, $F = 3.47$, $p < .001$), statistical models ($R^2 = .182$, $F = 2.76$, $p = .001$), concluding research ($R^2 = .144$, $p = .018$), and data interpretation ($R^2 = .133$, $p = .033$). Data entry was marginal ($R^2 = .134$, $p = .031$).

The three retained challenges from Table 3 showed the strongest model fit: Software (22.7% variance explained, adjusted $R^2 = 16.5\%$), computer skills (21.9%, adj. 15.6%), and models (18.2%, adj. 11.6%), exceeding the 13%. The remaining seven models were non-significant ($p = .063$ to $.595$), with $R^2 = .065$ to $.122$ and adjusted R^2 near zero or negative, indicating that supervisor guidance and university collectively did not predict those challenges beyond chance. This pattern validates the decision to focus interpretation on the three robust models where institutional differences persisted after controlling for guidance quality.

Table 5: Significant Predictors of Research Challenges from Multiple Regression Models with Variance Inflation Factor Diagnostics

Outcome	Predictor	B	SE	CI95	p	VIF
Software	University MU vs BU	0.80	0.19	[0.42,1.18]	<.001	1.45
Software	Guidance Data Entry	-0.29	0.14	[-0.57,-0.01]	.041	2.10

Models	University MU vs BU	0.95	0.18	[0.60,1.30]	<.001	1.45
Computer	University MU vs BU	-0.70	0.22	[-1.13,-0.27]	.002	1.45
Interpretation	University MU vs BU	0.49	0.23	[0.04,0.94]	.034	1.38

Table 5 presents only significant predictors ($p < .05$) from the three retained regression models, with VIF diagnostics confirming no multicollinearity (all VIF < 2.10 , well below threshold of 5).

University was the dominant predictor. MU students reported significantly higher challenges than BU students in data analysis software ($B = 0.80$, 95% CI [0.42, 1.18], $p < .001$) and statistical models ($B = 0.95$, 95% CI [0.60, 1.30], $p < .001$) after controlling for all 12 supervisor guidance items. This effect persisted independently of guidance quality, indicating institutional-level factors (e.g., software licensing, statistics training, lab infrastructure) rather than supervisor differences. Conversely, BU students reported higher computer skills challenges ($B = -0.70$ for MU vs BU, 95% CI [-1.13, -0.27], $p = .002$), suggesting MU has stronger basic ICT support.

Supervisor guidance effect: Only one guidance item was significant: higher guidance on data entry predicted lower software challenges ($B = -0.29$, 95% CI [-0.57, -0.01], $p = .041$). Each one-unit increase in data entry guidance reduced software challenge by 0.29 units, suggesting hands-on data management support transfers to software confidence. No other guidance items (11 of 12) significantly predicted challenges ($p > .05$), indicating that while guidance is important, university-level resources are stronger determinants of methodological challenges.

Hypothesis Test Results

The null hypothesis (H_0 : no institutional difference) was rejected for domain-specific challenges (computer skills, software, statistical models, data entry). However, the alter-native hypothesis of uniform superiority of one format was not supported. Instead, the BU individual format correlated with computer/report challenges; the MU group format correlated with software/modeling challenges. Effect sizes were medium-to-large for three of four significant differences.

DISCUSSION

Summary of Key Findings

Institutional differences in domain-specific bottlenecks, not uniform superiority. BU context (individual-associated) Medium challenge in computer skills. MU context (group-associated) Medium challenge in software/models. Front-end tasks Low at both. Because university is confounded with format, we cannot determine causality. We hypothesize: Individual-associated contexts may privilege ICT self-sufficiency; Group-associated contexts may privilege technical coordination. These are tentative hypotheses.

Interpretation

Results align with scaffolding theory and prior findings on UR outcomes. Individual students lack peers to distribute computer work, making ICT competence a gatekeeper to assessment success—consistent with Vygotsky's prediction that collaborative learning provides scaffolding absent in individual tasks [6]. Group students can divide labor but face coordination costs on technical tasks, consistent with transaction cost models of teamwork and documented benefits of UR for developing collaboration skills [7].

The absence of guidance $\times$ university interactions suggests training needs may be structural rather than purely pedagogical. This extends work showing that supervisory relationships require “fit” between student needs and supervision activities, and that good supervision is context-dependent rather than universal [11, 12].

Theoretical Implications

Findings extend Astin’s I-E-O model: environment—here, project format (or institutional practices surrounding format)—directly shapes which inputs become critical for assessment success [2]. Constructivist theory predicts that students construct knowledge through tasks; our data suggest that task structure determines which knowledge gets constructed and assessed. Future models of UR should treat format as a moderator, not a main effect, building on foundational work on doctoral supervision concepts and the integration of research and teaching [4,8].

Revised Propositions

- 1) Individual project formats may privilege ICT self-sufficiency; students without strong computer skills face disproportionate barriers.
- 2) Group project formats may privilege technical coordination; students must master software and modeling tasks that become visible during collaborative work.
- 3) Institutions should align scaffolding to format-specific bottlenecks rather than adopt one-size-fits-all training.

Practical Implications

BU should implement mandatory computer skills modules before the project stage, targeting report compilation and basic analysis software. This addresses the high ICT barrier documented in this institutional context. MU should formalize technical role allocation in groups: data manager, analyst, and writer. This addresses coordination challenges documented at this institution.

Both institutions should use diagnostic surveys to assign targeted workshops, as perception gaps between students and supervisors were large and domain-specific [5, 8, 10]. Supervisor training should address these gaps using models of supervisory fit and under-graduate project coordination [9, 10].

LIMITATIONS AND FUTURE RESEARCH

Critical limitation: The design confounded university with project format; we cannot determine whether observed differences reflect format, institutional culture, resources, curriculum, national context, or their interaction. Future multi-institution studies within the same country, or within institutions using both formats, are needed.

Additional limitations include that the cross-sectional data preclude causal claims. Self-report may also inflate or deflate reported challenges, and single-item measures may have limited reliability. Furthermore, omitted variables such as prior GPA, gender, and age may confound the findings, and the absence of performance measures means the self-reported challenges cannot be validated against objective outcomes.

Future research directions

Future research directions include longitudinal designs that track students through project completion and use performance measures such as grades and completion time as outcomes; within-institution comparisons of individual versus group formats; and randomized format assignment where ethically and practically feasible. They also involve testing interventions derived from the priorities in Table 4, conducting qualitative studies to understand the mechanisms underlying observed differences, and carrying out multi-country studies to assess generalizability.

CONCLUSION

While institutional contexts were associated with distinct profiles, the confounded design means institutional factors may equally explain differences. With this caveat, contexts associated with individual formats showed ICT challenges; group-associated showed technical coordination challenges.

Universities should align scaffolding to bottlenecks. This approach is hypothesis-generating. If validated by future studies linking self-reported challenges to actual performance metrics such as grades and completion time, targeted scaffolding may have implications for completion and quality. Future within-institution comparisons needed.

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