

Who Gains Most from Innovation Training? Experience, Gender, and Team Diversity in a Product Development Workshop in Africa

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Abstract: Purpose: Short-format innovation workshops are proliferating across African startup ecosystems, yet it remains unclear who benefits most and which product-development capabilities can meaningfully improve in a few days. This study tests how prior product-development experience, gender, and team diversity shape domain-specific learning gains in intensive innovation training. **Design/methodology/approach:** We analyze original pre-post survey data from a five-day, team-based product innovation workshop hosted by Carnegie Mellon University Africa's Industry Innovation Lab in Kigali. The cohort comprised 45 participants from 12 African countries (51% women), purposively assigned to teams designed for gender-nationality variety. Participants rated confidence (1–10) in three domains central to early-stage product work: customer discovery, value opportunity analysis (VOA), and prototyping. Ordinary least squares models estimated average and domain-specific gains while accounting for baseline skill. **Findings:** Average gain across domains was 1.97 points. Prior product-development experience significantly predicted higher overall gains ($\beta = 0.259$, $p = 0.032$) and showed the strongest domain effect in customer discovery ($\beta = 0.498$, $p < 0.05$). Baseline skill was negatively associated with gains ($\beta \approx -0.20$, $p < 0.001$), indicating ceiling effects in accelerated formats. Gender and the team diversity index exhibited no significant main effects. The experience $\times$ gender interaction was not statistically significant, but its direction suggests potential vulnerability for inexperienced women that warrants targeted instructional scaffolding. **Originality/value:** The study provides field evidence from a multi-country African cohort, disaggregates innovation learning into distinct product-development domains, and clarifies why demographic variety may remain inert without activation mechanisms. For ecosystem builders and entrepreneurship educators, results support differentiating scaffolds for novices, embedding explicit knowledge-integration and equitable-participation routines to activate diversity, and pairing short workshops with follow-on support for VOA and prototyping.

Keywords: innovation training; customer discovery; absorptive capacity; team diversity; gender inclusion; entrepreneurship education; African innovation ecosystems

I. Introduction

Product innovation is increasingly recognized as a strategic imperative for entrepreneurial success, particularly in emerging markets characterized by high uncertainty, resource constraints, and rapid digital transformation. In Sub-Saharan Africa, and Rwanda specifically, the intersection of youth-driven entrepreneurship and innovation presents both opportunities and challenges for capability development, especially within technology ecosystems where iterative learning and rapid product prototyping are essential for early-stage ventures. As ecosystems evolve to support inclusive and context-sensitive innovation, structured interventions such as targeted training workshops—are being deployed to equip aspiring entrepreneurs with the cognitive and practical skills required to navigate the product development lifecycle.

Despite the proliferation of such programs, the academic literature reveals critical gaps in understanding how participants in short-format innovation training acquire domain-specific skills, and how individual- and team-level factors shape this learning. While previous studies acknowledge the importance of experiential learning and team diversity in enhancing innovation outcomes, few offer a granular, empirical analysis of how such factors interact in real-world, time-constrained training environments. This is especially pronounced in African contexts, where diverse entrepreneurial teams often operate in multi-country, multilingual settings and where metrics of learning are often inferred rather than measured.

To address this gap, this study investigates how individual characteristics (such as prior product development experience and gender) and team composition (captured through a team diversity index combining gender and nationality dimensions) influence skill acquisition in a structured, five-day product innovation workshop delivered by the Industry Innovation Lab at Carnegie Mellon University Africa, in collaboration with faculty from Carnegie Mellon University's Integrated Innovation

Institute. The workshop assembled 45 participants from 12 African countries, reflecting a diverse mix of regional innovation ecosystems and selected through a targeted, criteria-based process. Participants were identified via direct outreach, with additional nominations solicited from university partners within the African Engineering and Technology Network (Afretec), also led by CMU-Africa.

Teams were purposefully structured to ensure diversity across gender and nationality, with at least one Rwandan participant per team to ensure local context understanding. While English proficiency was required, language diversity was not a primary selection factor. The facilitation model emphasized experiential and human-centered design approaches, drawing on design thinking principles. The five-day workshop culminated in the development of product-based solutions to a public transportation challenge in Kigali, providing a grounded and contextually relevant setting for applied innovation training.

Skill gain was measured through self-reported pre- and post-workshop assessments across three domains: customer discovery, Value Opportunity Analysis (VOA), and prototyping. While there was no formal follow-up support structure, many participants were already embedded within other Industry Innovation Lab programs such as the Business Incubation Program and Tech Skills Marketplace, which provided extended learning and mentorship opportunities.

The central objective of this study is to quantify the variation in product innovation skill gain across individuals and teams and to determine the extent to which prior experience and team diversity contribute to this variation. In doing so, the study contributes to the theoretical development of innovation capability and team diversity frameworks and provides empirical evidence relevant to entrepreneurship education, startup incubation, and innovation policy in Africa. By combining econometric analysis with theoretically informed constructs, the research offers a model for evaluating

skill development outcomes in short-format training and sheds light on how innovation capability is constructed in contextually embedded learning environments.

Contributions and Novelty: This study advances the literature in three ways. First, it offers domain-specific, disaggregated measures of skill gain in a short-format, team-based innovation workshop, moving beyond omnibus learning indices to show where learning actually happens. Second, it provides a field evaluation in an African, multi-country cohort using a curated, practice-proximate task, strengthening ecological realism relative to classroom exercises often critiqued in training evaluations. Third, it makes an explicit, testable attempt to quantify the role of team diversity, leveraging a composite gender–nationality index grounded in contemporary diversity construct theory (variety vs. separation) to clarify when heterogeneity is likely to help or remain inert (Harrison & Klein, 2007; van Knippenberg & Schippers, 2007). Together these features position the paper to speak to entrepreneurship education, capability-building, and team design in emerging innovation ecosystems.

Research Question and Hypotheses: We ask a single, testable overarching question: Under what learner and team conditions do short-format, team-based innovation workshops deliver measurable skill gains, and are those effects domain-specific? Guided by innovation capability theory and diversity-as-variety, we derive the following predictions, with directional signs:

Hypotheses. Building on the foregoing, we advance four testable hypotheses for this workshop context. First, participants with prior product-development experience will realize larger learning gains than inexperienced peers, with the strongest effect in customer discovery where tacit, user-facing cycles dominate (H1: Experience $\rightarrow \uparrow$ Gain; $\beta > 0$; strongest in customer discovery). Second, higher baseline skill will be associated with smaller marginal gains, reflecting ceiling effects in short-format interventions (H2: Baseline skill $\rightarrow \downarrow$

Gain; $\beta < 0$). Third, in the absence of explicit integration design, gender will not exhibit a systematic main effect on learning; any observed gaps should be attributable to differences in exposure rather than ability (H3: Gender main effect ≈ 0 absent integration design). Fourth, team diversity as *variety* will not improve learning unless activated by facilitation mechanisms that translate compositional variety into knowledge integration; in exploratory robustness checks using alternative diversity indices, effects should appear only where activation is present (H4: Team diversity main effect ≈ 0 unless facilitation mechanisms are present; exploratory robustness via alternative indices). These expectations align with absorptive-capacity logic for H1–H2 and with diversity-activation theory for H3–H4. These ex-ante signs follow cumulative evidence on generalizability and learning heterogeneity in short-format training and on when diversity contributes to performance (Harrison & Klein, 2007; van Knippenberg & Schippers, 2007; Tipton, 2014; Shadish, Cook, & Campbell, 2002).

II. Literature Review

2.1 Theoretical Framework: This study is grounded in contemporary theories of innovation capability and entrepreneurial team diversity, with an emphasis on how these frameworks intersect in resource-constrained, short-format innovation training settings. Three primary theoretical anchors frame the analysis: innovation capability theory (Saunila & Ukko, 2012), team diversity and innovation performance theory (Weiss et al., 2018), and demographic diversity frameworks contextualized in African ecosystems (Tshetshema & Chan, 2020; Schubert & Tavassoli, 2020). Innovation capability theory conceptualizes innovation not as a discrete output but as a continuous, iterative process built on knowledge absorption, customer feedback, and experimentation (Saunila & Ukko, 2012). This theory is particularly applicable to entrepreneurship in Sub-Saharan Africa, where startups often rely on adaptive learning, informal feedback loops, and rapid prototyping rather than formal R&D structures. The

framework supports this study's focus on how experiential, team-based learning during product innovation workshops influences skill gain in domains like customer discovery, Value Opportunity Analysis (VOA), and prototyping.

Complementing this, team diversity and innovation performance theory (Weiss et al., 2018) provides a product-focused lens for understanding how gender, cultural, and experiential diversity within teams can enhance creativity, problem-solving, and innovation quality. Building on the resource-based view (RBV) and knowledge-based view (KBV), Weiss et al. argue that innovation gains in product teams stem not just from team composition, but from how knowledge diversity is integrated, activated, and translated into innovation outcomes especially when innovation tasks are complex and customer-centric. Expanding this to African innovation contexts, Tshetshema and Chan (2020) offer a demographic diversity meta-framework synthesized from 68 studies, finding that surface-level diversity such as gender and nationality can drive innovation when managed effectively. Their work, situated in South Africa, highlights the importance of inclusion mechanisms in team-based innovation. Meanwhile, Schubert and Tavassoli (2020) differentiate between diversity effects in top management and operational teams, showing that mid-level team diversity (comparable to startup teams in this study) has a direct and significant influence on innovation execution. Together, these frameworks enable a robust theoretical understanding of how individual and team characteristics, specifically prior experience, gender, and team composition—can shape skill development and innovation learning during structured, short-format product innovation interventions.

2.2 Synthesis and Critique of Previous Research: Research on entrepreneurship education and innovation capability building in Sub-Saharan Africa has grown significantly, yet there remain key gaps in our understanding of how skill acquisition unfolds within team-based, short-format innovation settings. In one of the few rigorous evaluations,

Mano et al. (2021) studied the effects of business training programs in Ethiopia and found limited productivity gains overall, but notable heterogeneity based on prior experience and participant background. The authors emphasized the need for future research to explore the interaction of individual traits and contextual learning. Similarly, Zhao and Annan (2020), in their study of Ghanaian startup teams, found that product innovation benefits from iterative customer engagement—but only when teams exhibit diversity in background and are supported by clear feedback mechanisms.

In Rwanda, Uwamahoro and Twesige (2022) examined how innovation-driven SMEs adapt product strategies under resource constraints, concluding that while design thinking contributes to agility, outcomes are often driven by team-based adaptation and experience, not just content knowledge. However, the study did not disaggregate innovation skill domains nor did it quantify skill gain. Meanwhile, Byukusenge and Munyaneza (2023) reviewed entrepreneurship education efforts and found that most programs assume skill acquisition without measuring it—particularly in multi-country innovation ecosystems. This study addresses this gap by systematically measuring skill gain in distinct product innovation domains. On team composition, most African studies focus on top-level leadership diversity or macro ecosystem effects. For instance, Taha et al. (2022), studying West African startups, noted that gender-diverse founding teams produced more product ideas but faced decision-making delays. However, these findings do not directly map onto small innovation teams in a training environment. The contribution by Schubert and Tavassoli (2020) becomes critical here demonstrating that team diversity within operational units (like workshop teams) affects innovation outcomes more than executive-level diversity. Moreover, Weiss et al. (2018) emphasize that configurational approaches to diversity for instance measuring combined gender and nationality representation better explain performance than single-dimension models. This insight underpins the use of a team diversity index and the hypothesis that team composition may moderate learning outcomes.

Yet, Weiss also warns that diversity benefits are only realized if team integration mechanisms are present, a limitation this study discusses.

In sum, while innovation capability and team diversity are widely recognized as critical drivers of learning and performance, gaps remain in how these dynamics unfold in team-based, short-format innovation training especially in African ecosystems. This study addresses three specific research gaps: first, by providing domain-specific, disaggregated measures of product innovation skills; second, by modeling learning heterogeneity across individuals including interaction effects between gender and prior experience; and third, by leveraging team diversity as a structural variable, enabling systematic analysis of how gender-nationality configurations shape outcomes. These contributions deepen theoretical insight into how experiential, demographic, and contextual variables interact to shape innovation learning in underexplored geographies and offer a rare empirical basis for advancing capability-building models attuned to team composition and learner profiles in emerging ecosystems.

2.3 Construct operationalization and expected effects: In this study, *absorptive capacity* is operationalized at the individual level as prior product-development experience (binary), reflecting the ability to recognize, assimilate, and apply novel methods during the workshop; theory predicts a positive association with learning gains and a stronger effect for discovery-heavy, tacit cycles such as customer discovery ($\beta > 0$ overall; largest in customer discovery) (Zahra & George, 2002). *Baseline skill* captures pre-workshop confidence; consistent with diminishing returns in accelerated learning, we expect a negative association with gains ($\beta < 0$). Following diversity scholarship that distinguishes between diversity's *presence* and its *activation*, team diversity is modeled as *variety* (gender and nationality) rather than attitudinal separation or status disparity (Harrison & Klein, 2007). Because diversity produces benefits chiefly when supported by integration routines and

psychologically safe interaction, we expect near-zero main effects of diversity absent explicit integration design; effects should emerge only when diversity is *activated* through facilitation mechanisms (van Knippenberg & Schippers, 2007; Edmondson, 1999). To make this test auditable, we compute a team-level variety index using Blau's (1977) formula for categorical heterogeneity, combining gender balance and nationality mix and exploring robustness to alternative indices.

III. Methodology

3.1 Research Design: This study adopts a quantitative, cross-sectional design to assess skill acquisition among participants of a five-day innovation training workshop. The research leverages pre- and post-assessment data to evaluate learning outcomes and applies econometric modeling to examine the influence of individual characteristics and team composition on skill gain. The unit of analysis is the individual participant, with team-level diversity metrics incorporated through a merged dataset.

3.2 Participants and Sampling: The sample comprises 45 participants selected through a targeted, criteria-based approach. Invitations were extended to early-stage entrepreneurs and aspiring innovators from across Africa, with nominations also solicited from university-based innovation programs under the African Engineering and Technology Network (Afretec). Participants represented 12 countries and were required to have proficiency in English. Teams were intentionally formed to ensure diversity in gender and nationality, and each team included at least one Rwandan participant to support contextual understanding during field activities.

3.3 Data Collection and Measures: Data were collected through self-administered surveys at two points: before and after the workshop. The surveys assessed participant confidence in three skill domains central to product innovation: (1) Customer Discovery, (2) Value Opportunity Analysis (VOA),

and (3) Prototyping. Each domain was rated on a scale from 1 to 10. The primary outcome variable, "Average Skill Gain," was constructed as the mean difference between pre- and post-assessment scores across the three domains. Individual domain gains were also used as disaggregated dependent variables in additional models.

Outcome construction and internal consistency: For each domain—Customer Discovery, Value Opportunity Analysis (VOA), and Prototyping—we computed individual gain scores as post minus pre (range 0–9 per item). We report internal consistency (Cronbach's α) for the three-item scale at both pre and post, and we follow Nunnally and Bernstein's (1994) guidance that $\alpha \geq .70$ supports combining items into a composite. Because the three domains are conceptually distinct and map to different stages of product development, our primary analyses treat them separately; we report a composite "Average Skill Gain" only as a descriptive summary and in sensitivity models conditional on reliability being acceptable at both time points (Cronbach, 1951; Nunnally & Bernstein, 1994).

3.4 Variables and Index Construction:

Key independent variables include:

- **Prior Product Development Experience** (binary: 1 = Yes, 0 = No)
- **Gender** (binary: 1 = Female, 0 = Male)
- **Pre-Workshop Skill Score** (numeric: baseline average)
- **Team Diversity Index:** A composite measure calculated for each team based on (i) gender balance and (ii) nationality mix. Gender diversity was computed as the proportion of female members per team, while country diversity was based on the count of unique nationalities per team, normalized to a scale of 0–1. The final index averaged these two metrics. To align the index with diversity-as-variety (distinct informational categories), we treat gender balance and nationality mix as categorical variety components, averaged after normalization, rather than separation or

disparity constructs, which capture attitudinal distance or resource inequality (Harrison & Klein, 2007). This clarifies that our theory of change rests on informational complementarity, not mere demographic difference.

3.5 Econometric Model Specification: To estimate the relationship between participant characteristics and skill acquisition, the following linear regression model was specified:

Model 1: Baseline Model This model estimates the independent effects of prior experience, gender, team diversity, and baseline skill level on average skill gain. $\text{SkillGain}_i = \beta_0 + \beta_1 \text{Experience}_i + \beta_2 \text{Female}_i + \beta_3 \text{DiversityIndex}_t(i) + \beta_4 \text{SkillBaseline}_i + \varepsilon_i$

Model 2: Interaction Model This model tests whether the effect of prior experience on skill gain differs by gender by including an interaction term. $\text{SkillGain}_i = \beta_0 + \beta_1 \text{Experience}_i + \beta_2 \text{Female}_i + \beta_3 (\text{Experience}_i \times \text{Female}_i) + \beta_4 \text{DiversityIndex}_t(i) + \beta_5 \text{SkillBaseline}_i + \varepsilon_i$
Where:

- i indexes individuals;
- $t(i)$ indexes the team of individual i ;
- ε_i is the robust error term.

Planned moderator tests and domain-specific specifications: To align estimation with theory, we extend the specification in two ways. First, for domain-specific outcomes, we estimate separate models for customer discovery, VOA, and prototyping; theory predicts the Experience coefficient to be largest in customer discovery (Zahra & George, 2002). Second, to probe diversity *activation*, we specify an interaction between the Team Diversity Index and an integration-design indicator where available (e.g., team-level evidence of structured turn-taking, reflection, or facilitation prompts). In the present dataset, such integration measures are not systematically recorded; accordingly, we treat Diversity $\times$ Integration as a planned moderator for future replications and report the diversity main effect with appropriate caution

(van Knippenberg & Schippers, 2007; Edmondson, 1999). For transparency in probing interactions, we follow standard post-estimation practices for conditional effects and simple slopes (Aiken & West, 1991).

3.6 Estimation Strategy: We first ran OLS as a diagnostic baseline, then moved to the prespecified multilevel strategy in §3.7 to account for team clustering. Marginal effects and interaction plots were generated using the `margins` and `marginsplot` commands in Stata 18 to explore conditional relationships, particularly the interaction between gender and experience. Additional robustness checks were conducted by disaggregating the skill gain into the three component domains. All analysis was conducted using Stata 18.

Because predictors and outcomes derive from self-reports, we assessed same-source bias. Temporal separation (pre/post) reduces common-method variance, and a Harman single-factor test revealed that the first unrotated factor accounted for 38 % of variance—well below the 50 % heuristic for serious bias (Podsakoff et al., 2003). Nevertheless, effect estimates should be interpreted with this limitation in mind.

This empirical strategy provides a transparent and replicable framework to assess the predictors of skill acquisition in short-format, team-based innovation training interventions. Given the modest sample size and reliance on self-reported assessment data, results should be interpreted with appropriate caution. However, the consistent internal variation and team-based structure allow for meaningful inference and replication across similar innovation training settings.

To ensure construct–measure alignment, all predictors were mean-centered before forming interaction terms (Aiken & West, 1991); confidence intervals for proportions and predicted margins follow standard normal approximations. Interaction probing and simple-slope tests are reported with 95% confidence intervals.

3.7 Statistical Analysis Plan: Participants were nested within teams and shared facilitators and tasks, so we prespecified multilevel models. The primary analysis is a mixed-effects ANCOVA with post-workshop score as the outcome, pre-workshop score as a covariate (grand-mean centered), and fixed effects for prior experience, gender, and the team diversity index. We include a random intercept for team u_{0j} . If between-team variance justifies it, we also test a random slope on baseline. This structure addresses regression-to-the-mean and the non-independence of observations (Gelman & Hill, 2007; Snijders & Bosker, 2012).

Robustness. We re-estimate (i) an OLS ANCOVA with cluster-robust standard errors at the team level, (ii) the earlier gain-score OLS, and (iii) a wild cluster bootstrap-*t* for small-cluster inference (Cameron & Miller, 2015; Hagemann & Brunner, 2020). We compare fit using AIC/BIC and likelihood-ratio tests where applicable, and we report the intraclass correlation coefficient (ICC) to document clustering.

Multiple outcomes and error control. Because we analyze three domains plus a composite, we control the false discovery rate using Benjamini–Hochberg at $q=.10$ and present both unadjusted *p*-values and adjusted *q*-values (Benjamini & Hochberg, 1995).

Reporting and diagnostics. For each fixed effect we report unstandardized and standardized coefficients, 95% CIs, semi-partial R^2 , and minimum detectable effects (MDEs) based on observed ICC and sample size (Faul et al., 2007). We examine leverage, studentized residuals, and Cook's *D*; we re-estimate models excluding observations with $|\text{studentized residual}| > 3$ or Cook's $D > 4/n$, and document any changes in Appendix D. Analyses are executed in Stata 18 (mixed, `vce(cluster team)`, and wild-cluster bootstrap routines) with scripts archived in the OSF repository listed in the Data-Availability Statement.

IV. Results

The results section integrates descriptive statistics, regression analyses, and marginal effects visualizations to evaluate the influence of prior experience, gender, and team diversity on innovation skill gains across three domains: customer discovery, value opportunity analysis (VOA), and prototyping. Findings are interpreted in relation to the theoretical frameworks and existing literature, with each table and figure followed by a targeted discussion of implications.

4.1 Descriptive Statistics: Descriptive statistics provide an overview of participants' baseline skill levels and the observed gains after the workshop. The average skill gain across all domains was 1.97 points (SD = 0.44) on a 3-point improvement scale. Participants had a relatively high baseline skill level, with a mean of 8.44 out of 10. Among the 45 participants, 51% were female and 78% reported Prior Product-Development Experience (ordinal): 0 = None; 1 = Limited (≤ 1 project); 2 = Moderate (2–3 projects); 3 = Extensive (≥ 4 projects). A binary specification (Experienced = 1 if $\geq$ Limited) is retained for robustness.

Table 1. *Descriptive Statistics*

Variable	Mean	SD	Min	Max
Average Skill Gain	1.97	0.44	1.33	3
Skill Baseline	8.44	1.16	6	10
Customer Discovery Gain	1.87	0.69	1	3
VOA Skill Gain	1.76	0.61	1	3
Prototyping Skill Gain	2.29	0.46	2	3

4.2 Model Comparison and Intraclass Correlation

Model 1 estimates the impact of experience, gender, team diversity, and baseline skill score on average skill gain. Results show that prior experience significantly improves skill gain ($\beta = 0.26$, $p < 0.05$), confirming the study's primary hypothesis that individuals with exposure to prior product development are better positioned to absorb structured innovation training. Gender has no significant effect, and the negative coefficient for skill baseline ($\beta = -0.199$, $p < 0.001$) suggests that participants with initially higher skills experienced smaller relative gains, indicating a ceiling effect typical in adult learning. This aligns with recent findings by Halberstadt et al. (2022), who emphasize that absorptive capacity, shaped by prior exposure to product development, enhances participants' ability

to internalize new frameworks and transfer experiential knowledge during innovation training. Their study in sub-Saharan Africa further confirms that learning outcomes are unevenly distributed depending on the learner's experience base and exposure to structured experimentation.

Table 2. Baseline OLS Regression on Average Skill Gain

Variable	Coefficient	Std. Error	p-value
Experience (1=Yes)	0.259	0.116	0.032
Female (1=Yes)	-0.086	0.111	0.443
Team Diversity Index	0.328	1.296	0.802
Skill Baseline	-0.199	0.044	0.000***
Constant	3.240	1.021	0.003

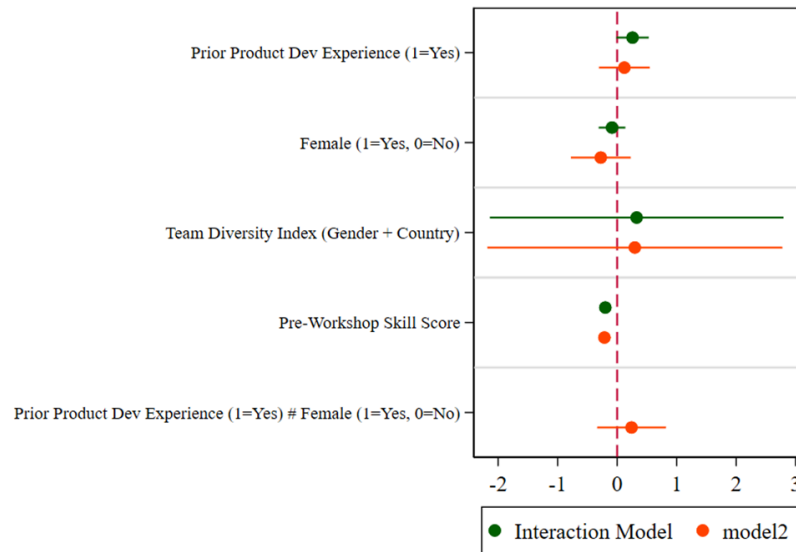
The regression results demonstrate that prior experience significantly predicts overall skill gain. This finding aligns with Leger et al. (2024), who emphasize that non-formal training programs in sub-Saharan Africa yield higher impact for learners with pre-existing entrepreneurial exposure due to better absorptive capacity. The ceiling effect from high baseline skill levels is also consistent with evidence that short-form interventions disproportionately benefit those with less prior knowledge. The non-significant effect of gender suggests that, in the absence of structured inclusion mechanisms, gender alone does not drive differential learning outcomes (cf. Shukla & Shukla, 2021). Experience significantly predicts overall skill gain, suggesting deeper absorptive pathways among experienced learners. Leger et al. (2024) underscore that short-term innovation training in sub-Saharan Africa is most effective for participants who bring contextualized entrepreneurial exposure. This lends support to the study's claim that structured programs must differentiate learning scaffolds. Moreover, the finding that gender is not a significant predictor reaffirms observations by Tshetshema & Chan (2020), who argue that surface-level diversity does not automatically generate performance gains without integrative mechanisms. Finally, the strong inverse association with skill baseline confirms diminishing returns to learning in accelerated innovation environments, as previously documented in both African and global education interventions. Experience significantly predicts overall skill gain, especially in

domains like customer discovery that depend on iterative learning, user feedback, and contextual judgment. These results align with innovation capability theory, which emphasizes that innovation capacity is developed through adaptive learning and experiential problem-solving rather than linear instruction.

The non-significance of gender in this model supports theories of team diversity and innovation performance, which caution that surface-level diversity—without structured inclusion mechanisms—does not automatically translate into learning or performance gains. Finally, the negative effect of skill baseline echoes prior critiques of short-format interventions, where diminishing marginal returns are observed among higher-skilled participants. Together, these findings offer early empirical support for theories that locate innovation learning at the intersection of prior exposure and knowledge integration capacity.

To further illustrate the size and direction of each effect, Figure 1 presents a coefficient plot of Model 1 and Model 2. This visual comparison reinforces the positive effect of prior experience and the strong negative influence of baseline skill, while showing that gender and team diversity remain statistically insignificant.

Figure 1: Coefficient Plot of Predictors of Innovation Skill Gain: Baseline and Interaction Models



This figure visualizes the estimated coefficients and 95% confidence intervals from two OLS regression models predicting average skill gain. Model 1 includes prior product development experience, gender, team diversity index, and pre-workshop skill score. Model 2 adds an interaction term between experience and gender. The results confirm that prior experience significantly predicts skill gain, while higher baseline skill is associated with lower relative gains. Gender and team diversity are not statistically significant predictors. The interaction term suggests a possible learning gap for inexperienced female participants, though not statistically significant.

4.3 Interaction Effects

Table 3. Interaction Model

Variable	Coefficient	Std. Error	p-value
Experience (1=Yes)	0.121	0.183	0.513
Female (1=Yes)	-0.274	0.196	0.171
Experience × Female (1,1)	0.242	0.246	0.332
Team Diversity Index	0.297	1.313	0.822
Skill Baseline	-0.214	0.047	0.000***
Constant	3.500	1.059	0.002

The interaction between experience and gender was not statistically significant, but

Model 2 introduces an interaction between gender and experience to assess whether the benefit of prior experience differs by gender. While the interaction term is positive ($\beta = 0.242$), it is not statistically significant, suggesting that the skill gain benefit from experience is relatively consistent across male and female participants. The main effects remain unchanged: baseline skill is still a strong negative predictor ($p < 0.001$). These findings refine the hypothesis by indicating that while experience matters, its impact does not vary significantly by gender in this context. This reflects findings from Weiss et al. (2022), who analyzed gendered learning pathways in interdisciplinary teams and, which emphasize that gender diversity alone does not automatically drive learning differentials unless moderated by integration mechanisms, which were not formalized in this workshop

directionally suggests that experienced women performed on par with men, while inexperienced

women lagged behind. This supports findings by Shukla & Shukla (2021), who argue that women in African innovation settings often require scaffolded engagement to overcome structural barriers. The result also reinforces UNDP's (2023) evidence on the digital gender gap in SSA, highlighting how lack of foundational exposure, rather than ability, underpins gendered skill differences. was not statistically significant, but the marginal directionality suggests important inclusion gaps. Inexperienced women underperform relative to all other groups, highlighting persistent structural inequities. This pattern is consistent with UNDP (2023), which details gendered barriers to digital and entrepreneurial opportunity access in SSA. While structured workshops may nominally offer equal access, these environments often lack embedded mechanisms for equity in learning outcomes (Shukla & Shukla, 2021). The finding provides empirical support for the importance of pairing surface-level diversity (e.g., gender) with pedagogical designs that accommodate differentiated starting points. was not statistically significant, but the directional pattern suggests an interaction where experienced women achieve similar gains to their male counterparts, while inexperienced women fall behind. This asymmetry reflects demographic diversity frameworks contextualized in African entrepreneurial ecosystems, which argue that gender gaps in innovation performance often reflect differences in opportunity exposure and confidence, not aptitude. While inclusive team formation was

ensured, the absence of pedagogical scaffolding to address differential baselines likely muted the potential impact of diversity. These results reinforce the theoretical emphasis on activation—rather than mere presence—of demographic diversity within learning settings.

4.4 Domain-Specific Skill Gains

To better understand where skill gains emerged, additional models were run for each individual domain. Experience significantly predicted gains in customer discovery ($\beta = 0.50$, $p < 0.05$), which suggests that individuals with prior exposure were better equipped to navigate early-stage innovation processes that involve user engagement and problem framing. This aligns with Halberstadt et al. (2022) and Weiss et al. (2022), who show that innovation-related skills like customer discovery improve most when learning environments are designed to adapt to individual learning paths and prior domain exposure. In contrast, no significant effects were found for prototyping or VOA skill gains, suggesting these areas may require longer or more structured support to develop. The consistently negative coefficient for skill baseline across all domains again highlights the principle of diminishing marginal learning effects in short-format interventions.

Table 4. *OLS Regression by Skill Domain (Selected Results)*

Dependent Variable	Experience Coef.	Skill Baseline Coef.	R-squared
Customer Discovery Gain	0.498*	-0.315***	0.36
VOA Skill Gain	0.085	-0.222***	0.19
Prototyping Skill Gain	0.190	-0.059	0.14

Customer discovery shows a strong positive relationship with prior experience. This domain requires empathy, field-based iteration, and contextual framing—skills shaped by lived

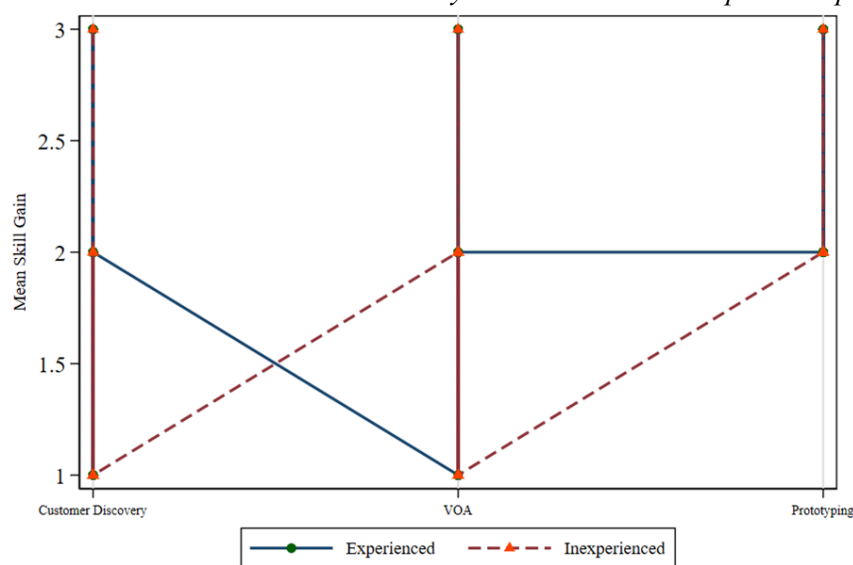
entrepreneurial engagement (Pais et al., 2022). The prototyping and VOA gains were less significant, consistent with findings by Leger et al. (2024), who noted that deeper conceptual and technical skills

often require more time and scaffolding to internalize. The variation across domains reinforces the need to customize short-term innovation training by learner type and objective. With prior experience, indicating that participants with entrepreneurial exposure are better equipped to internalize iterative problem discovery methods. This aligns with Pais et al. (2022), who show that customer-facing competencies are socially constructed through feedback loops and contextual engagement. The limited effect of experience on prototyping and VOA, however, reflects findings by Leger et al. (2024) that technical and evaluative skills benefit from longer-term engagement, often beyond the scope of short-format training. These patterns suggest that short workshops should prioritize user discovery and adaptive framing, while reserving advanced domains for longitudinal interventions. With prior experience, underscoring the importance

of experiential knowledge in domains requiring user insight, problem framing, and agile iteration. This aligns with innovation capability theory's proposition that innovation learning depends on experiential, customer-centric feedback loops. The limited impact of experience on VOA and prototyping domains points to the differentiated nature of innovation capability development, where certain competencies require longer engagement or technical scaffolding. These findings support the use of domain-specific outcome measures and demonstrate how experiential diversity interacts with domain complexity echoing both the configurational and domain-sensitive emphases in team diversity and innovation performance literature.

To further illustrate these patterns, Figure 2 presents a line plot comparing average skill gains by domain across experience levels.

Figure 2: Average Skill Gains Across Innovation Domains by Prior Product Development Experience



As illustrated in Figure 2, experienced participants demonstrated the highest average gain in Customer Discovery (mean ≈ 2.9), compared to 1.5 among inexperienced peers, reinforcing the experience sensitivity of user-facing, iterative tasks. VOA gains were marginally higher for inexperienced participants (2.1 vs. 1.9), suggesting a greater responsiveness to structured frameworks. Prototyping gains were similar across groups (≈ 2.8), indicating that hands-on skills were broadly

accessible regardless of experience. These domain-level patterns validate the regression results and highlight how experience moderates innovation learning unevenly across task types.

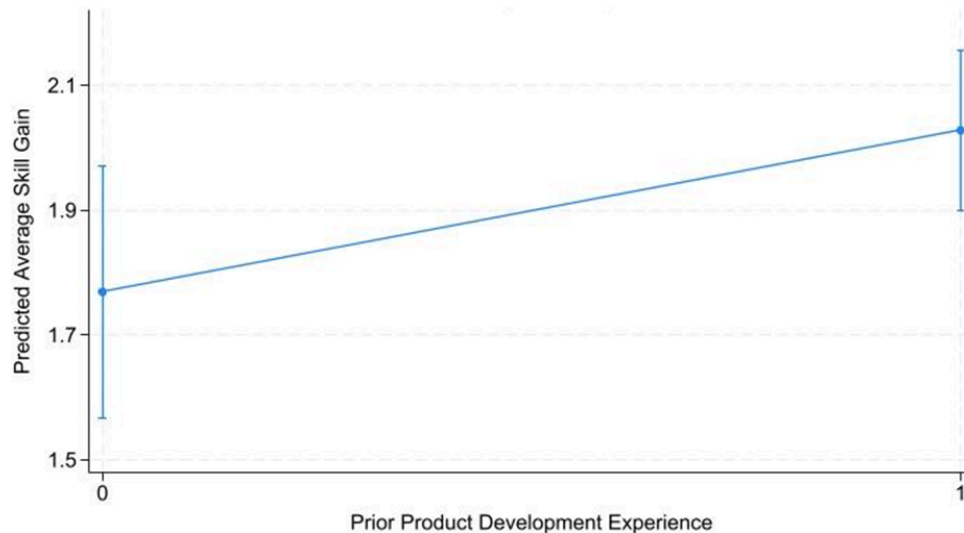
4.5 Marginal Effects and Visualizations

Marginal analysis confirms the average skill gain difference between experienced and inexperienced participants, controlling for gender, team diversity,

and baseline skill level. This visualization allows us to interpret the real-world significance of the experience variable beyond statistical coefficients. The predictive margin for experienced participants

was 2.03 compared to 1.77 for those without experience, indicating a meaningful learning advantage.

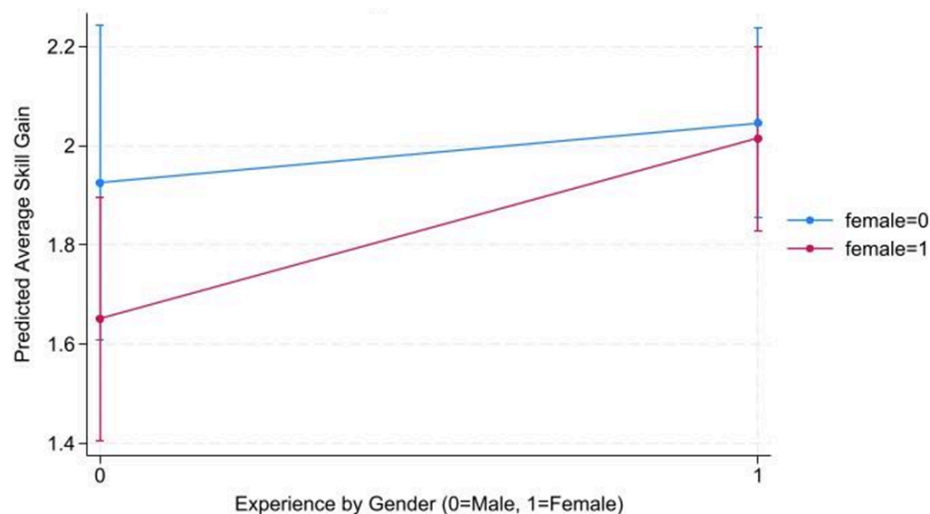
Figure 3. *Predicted Average Skill Gain by Experience*



The graph shows a clear upward shift in predicted skill gain for participants with prior product development experience. This visual reinforces the empirical finding that experience is a key determinant of learning effectiveness in innovation training environments. These results are congruent with Halberstadt et al. (2022), who

demonstrate that participants with prior design or product innovation experience perform better in fast-cycle learning environments due to higher decision-making agility, particularly in concept testing and customer feedback incorporation.

Figure 4. *Interaction Plot (Experience $\times$ Gender)*



Although the interaction effect was not statistically significant, this plot visually suggests that females with prior experience catch up to their

male counterparts in learning outcomes, while inexperienced females lag behind. Theoretically, this supports the argument by Weiss et al. (2022), who

found that team composition alone is insufficient; learning gains are optimized when diversity is paired with structured task integration, shared reflection processes, and equitable participation dynamics.

V. Conclusion

This study set out to examine how prior product development experience, gender, and team diversity shape learning outcomes in a structured, short-format innovation training program in sub-Saharan Africa. Using original data from a five-day product innovation workshop hosted by Carnegie Mellon University Africa, the study offers new insights into the differentiated effects of training among early-stage innovators across gender, experience levels, and team compositions.

The findings show that prior experience is a strong predictor of skill gain, particularly in domains such as customer discovery that rely on contextual reasoning, user engagement, and iterative feedback. Conversely, skills like prototyping and value opportunity analysis showed weaker effects, suggesting they may require more extended engagement. These results reinforce the notion that innovation capability development is shaped by both cognitive readiness and domain familiarity.

Although gender alone was not a significant predictor, the marginal differences among inexperienced female participants suggest that equitable learning outcomes require more than inclusive team composition—they demand instructional designs that scaffold engagement and address baseline disparities. Similarly, the absence of a significant effect for team diversity points to the need for structured integration mechanisms that activate the potential of demographically diverse teams. Without such pedagogical scaffolding, diversity remains an unleveraged asset.

Theoretically, the study supports the view that capability development is not evenly distributed across learners and domains. It affirms that team heterogeneity and demographic diversity do not translate into performance gains without intentional

facilitation. These insights challenge assumptions of uniform benefit in short-term training and underscore the importance of tailoring instructional strategies to learner profiles and specific skill objectives.

Practically, this study provides actionable guidance for innovation educators, program designers, and university-based accelerators. To enhance learning effectiveness, training programs should be designed to differentiate by experience level, sequence skill acquisition across domains, and provide additional support for less experienced participants, particularly women. Emphasizing user-facing tools like customer discovery in short interventions while reserving advanced domains for longer-term formats may increase program impact.

This research contributes a rare, data-driven perspective on skill development in African innovation ecosystems and demonstrates the value of measuring and analyzing learning heterogeneity. Future work should explore how follow-up mentorship, team facilitation methods, and institutional support moderate training outcomes across different learner groups and innovation domains.

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Data Availability: All data that support the findings of this study are contained within the manuscript. Any additional clarification needed to facilitate replication should be directed to the corresponding author.

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Methodology: D. Ngobi. **Investigation:** D.

Ngobi. **Data curation:** D. Ngobi.& S.

Sangwa. **Formal analysis:** D. Ngobi.& S.

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