Measuring the Impact of Targeted GIS Training on NGO Field Operations

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Abstract- Geographic Information Systems (GIS) have become indispensable tools for public health and humanitarian organizations, enabling effective planning, monitoring, and evaluation of field interventions. Despite the growing reliance on spatial data, many non-governmental organizations (NGOs) continue to struggle with data quality, operational efficiency, and integration of geospatial insights into decision-making. This study examines the impact of a structured GIS training program delivered to health field teams within the Hacey Health Initiative. Using a pre- and post-training design, the research measured changes in data accuracy, completeness, and collection efficiency during field operations. The intervention consisted of a targeted training curriculum incorporating ArcGIS Pro and Survey123, applied to routine health data collection processes. Data sources included field observation forms, device-generated logs, and quality control samples reviewed by supervisory staff. Accuracy audits were conducted on randomly selected data points, completeness was scored against standardized forms, and collection time metrics were captured from device logs. Results demonstrated statistically significant improvements across all indicators, with accuracy scores increasing by 21.4%, completeness rising by 18.7%, and average data collection time per case reduced by 27.5% following the training. These findings underscore the value of structured GIS capacity-building for NGOs, particularly in resource-constrained health programs, where data-driven decision-making is critical for optimizing outcomes. The study concludes with recommendations for embedding GIS training into NGO operational frameworks, aligning field practices with emerging standards in digital health and geospatial analytics.

Keywords: Geographic Information Systems, NGO Operations, Health Data Quality, Arcgis Pro, Survey123, Field Efficiency, Capacity-Building, Hacey Health Initiative

I. INTRODUCTION

1.1 Background and Rationale

The ability to collect, manage, and analyze high-quality spatial data has become central to the effectiveness of health and humanitarian interventions. Geographic Information Systems (GIS) provide a framework for capturing, storing, analyzing, and visualizing geographically referenced information, enabling stakeholders to identify service gaps, allocate resources, and monitor outcomes with spatial precision. For NGOs engaged in community health programs, GIS facilitates mapping of health service delivery points, tracking of outreach activities, and identification of underserved populations. Beyond operational logistics, GIS supports program evaluation by allowing stakeholders to examine relationships between health indicators, geographic access, and socio-demographic characteristics [1,2].

Despite its transformative potential, GIS adoption among NGOs is frequently constrained by limited technical capacity, inadequate training, and a reliance on paper-based or fragmented digital systems. Field staff are often tasked with data collection under challenging conditions, where competing demands on time, variable literacy with digital tools, and resource constraints affect both the quality and efficiency of data. Errors in geographic coordinates, incomplete entries, and prolonged collection times compromise the reliability of datasets, ultimately weakening evidence-based decision-making. Consequently, there is growing recognition that structured, context-specific GIS training could serve as a critical enabler for NGOs, enhancing both the accuracy of collected data and the efficiency of operations [3,4].

The advent of platforms such as ArcGIS Pro and Survey123 has lowered technical barriers by offering intuitive interfaces for field data collection, real-time validation, and integration with cloud-based systems. When paired with targeted training programs, these tools can significantly enhance the competencies of NGO field teams. However, empirical evidence quantifying the direct impact of GIS training on operational metrics, such as data accuracy, completeness, and collection time, remains limited, especially in resource-constrained contexts. While case studies and anecdotal reports suggest positive outcomes, rigorous pre- and post-intervention evaluations are scarce [5,6].

The present study addresses this gap by systematically evaluating the effects of targeted GIS training on the performance of health field teams working under the Hacey Health Initiative, a program delivering community-based health interventions. Using a pre-post design, the research examines whether structured capacity-building in GIS translates into measurable improvements in data quality and operational efficiency.

1.2 Problem Statement

The operational effectiveness of NGOs hinges on the ability to generate accurate, complete, and timely data from the field. Yet, in many low- and middle-income contexts, data collection is compromised by inconsistent training, limited technical infrastructure, and high turnover among field staff. These challenges manifest in three primary ways: first, errors in spatial accuracy, often due to improper use of GPS-enabled devices or incorrect entry of coordinates; second, incomplete datasets arising from skipped fields, misunderstanding of form requirements, or fatigue; and third, inefficiencies in data collection workflows, leading to prolonged time spent per case and reduced overall coverage (7,8).

While digital data collection platforms promise to mitigate some of these challenges, their success depends heavily on the competencies of end-users. Without adequate training, field staff may fail to exploit validation features, continue to rely on error-prone manual practices, or underutilize advanced geospatial functions. This undermines the potential of GIS to drive program effectiveness. Despite widespread recognition of these barriers, there is limited empirical evidence on whether structured GIS training can tangibly improve operational outcomes in NGO field contexts. Most available studies remain conceptual or descriptive, with few offering quantifiable evidence of impact (9).

The central problem, therefore, is the lack of rigorous, evidence-based assessments of GIS training interventions within NGO health operations. By addressing this gap, the current study seeks to provide actionable insights for NGOs, donors, and policymakers seeking to strengthen geospatial capacity in field programs.

1.3 Objectives of the Study

The overarching objective of this study is to evaluate the impact of a structured GIS training program on the operational performance of NGO health field teams. In pursuit of this aim, the study focuses on four specific areas of inquiry. The first is to assess changes in data accuracy, measured through independent quality control audits of field-collected records before and after the intervention. The second is to evaluate improvements in data completeness, using standardized scoring protocols applied to observation forms. The third is to measure differences in data collection efficiency, quantified through device log records that capture the time spent per completed form. The final objective is to explore the broader implications of GIS training for the scaling of digital health interventions within NGO contexts. Collectively, these objectives are designed to generate empirical evidence on whether targeted GIS capacity-building can lead to measurable improvements in both the quality of field data and the efficiency of operational workflows.

1.4 Significance of the Study

This research holds significance at multiple levels. For NGOs directly engaged in health service delivery, the findings provide practical evidence on the value of investing in GIS training as a strategy for improving field operations. By demonstrating measurable improvements in accuracy, completeness, and efficiency, the study offers a replicable model for integrating training into broader program workflows.
At a broader level, the study contributes to the literature on digital health, geospatial capacity-

building, and program evaluation. By adopting a pre-post design, it addresses the evidence gap surrounding the causal effects of GIS training interventions in resource-constrained NGO settings. This adds empirical rigor to policy discussions on scaling digital tools in global health programs [10,11].

Furthermore, the research aligns with international calls for strengthening the data ecosystems of NGOs and civil society organizations. Donors and governments increasingly expect program data to meet standards of accuracy, completeness, and timeliness comparable to those of formal health systems. By highlighting the role of GIS training in meeting these expectations, the study underscores its strategic relevance for NGO sustainability and accountability.
Finally, the study's focus on the Hacey Health Initiative provides a context-specific contribution, documenting how a mid-sized health NGO in a low-resource environment can leverage targeted training and mainstream digital platforms such as ArcGIS Pro and Survey123 to strengthen operations. The lessons derived have potential applicability for similar organizations across Africa and other regions where NGOs play a pivotal role in health service delivery.

II. METHODS

2.1 Research Design and Methodological Approach

The study employed a pre- and post-intervention design to evaluate the impact of structured GIS training on data quality and operational efficiency among NGO field teams. This design was selected because it allows for direct comparison of performance indicators before and after the intervention, thereby attributing observed changes to the training provided. A mixed-methods orientation was adopted, combining quantitative data drawn from audits, device-generated logs, and completeness scoring with qualitative insights from supervisory observations and debriefing sessions. This combination enabled both statistical testing of the research hypothesis and a nuanced understanding of how the training influenced field practices.

The study was embedded within the Hacey Health Initiative, a program that implements community-based health interventions across peri-urban and rural districts. Routine activities within this initiative include maternal and child health outreach, vaccination campaigns, adolescent health sessions, and monitoring of service utilization patterns. These activities rely heavily on systematic data collection across geographically dispersed sites, making them suitable for assessing the effects of GIS training on field performance. The central research question guiding the study was whether structured GIS training could improve data accuracy, data completeness, and the efficiency of data collection processes.

2.2 Study Setting and Participants

The research was carried out in three program clusters within southwestern Nigeria, where the Hacey Health Initiative has an established operational presence. Each cluster covered between fifteen and twenty communities, with a combined population estimated at 250,000 people. The selected setting provided a diverse mix of peri-urban and rural conditions, ensuring that the training was tested across varying levels of infrastructure, connectivity, and community access.

A total of forty-two field officers participated in the study. These officers were employed by the NGO and were directly responsible for the collection of health and program data during outreach activities. All participants had been involved in routine data collection for at least six months prior to the intervention, ensuring a sufficient baseline of experience. They were familiar with smartphones or tablets but had received no formal GIS training prior to the study. Participation in the training was voluntary, and informed consent was obtained. In addition to field officers, six supervisory staff members were involved in the process. These supervisors did not receive the training but were responsible for conducting independent audits and quality control activities before and after the intervention.

2.3 GIS Training Intervention

The training program was designed as a structured, five-day intervention aimed at equipping field teams with the knowledge and practical skills necessary to improve the quality and efficiency of GIS-enabled data collection. The curriculum was organized to balance theoretical foundations with hands-on application. Initial sessions introduced participants to fundamental GIS concepts, including coordinate systems, map projections, and the value of spatial analysis in public health programming. These sessions emphasized the relevance of GIS to the NGO's operational context, helping participants connect abstract concepts to their day-to-day responsibilities. Subsequent modules focused on ArcGIS Pro, where participants learned to create and manage geodatabases, edit and validate attribute tables, and generate maps for reporting purposes. Practical exercises involved manipulating real datasets drawn from previous program activities, which made the sessions immediately relevant. Another core component of the training was Survey123, the mobile data collection application integrated into the ArcGIS environment. Participants were guided through the process of designing digital forms, embedding validation rules, capturing GPS coordinates, and applying offline data collection strategies for low-connectivity settings. The training also emphasized synchronization of data with ArcGIS Online to ensure centralized storage and streamlined reporting.

Field simulations were integrated into the program. Under the supervision of trainers, participants conducted data collection exercises in nearby communities. This allowed them to apply new skills in realistic conditions and receive immediate feedback. Trainers emphasized common pitfalls in data collection, including errors in GPS capture, incomplete forms, and inefficient workflows. Discussions on data quality and operational efficiency were embedded throughout the program, ensuring that participants understood not only how to use the tools but also why accuracy, completeness, and timeliness mattered for program outcomes.

2.4 Data Sources and Collection

Data for the study were drawn from three complementary sources, each chosen to capture a different dimension of performance. The first source was field observation forms used during program activities. These forms included variables related to service delivery, demographic details, and outreach session records, and were assessed for completeness and consistency. The second source was device-generated logs from Survey123, which automatically recorded metadata such as timestamps for form initiation and submission, GPS coordinates, and synchronization events. These logs enabled the calculation of average collection times per case and provided insights into workflow patterns. The third source was quality control samples generated by supervisors. For each data collection period, supervisors independently verified approximately ten percent of records by re-collecting selected variables, including location coordinates and service counts, to serve as a gold standard for accuracy measurement.

Data were collected across two time periods to enable comparison. A four-week baseline period prior to the training served as the pre-intervention phase, during which field officers continued routine activities without GIS-specific instruction. Following completion of the five-day training, another four-week period was observed as the post-intervention phase. During this period, participants applied their new skills in real operational contexts, and the same indicators were measured for comparability. This design ensured that any differences observed between the two phases could reasonably be attributed to the training.

2.5 Measurement Indicators

Three primary indicators were assessed in order to determine the impact of the intervention: accuracy, completeness, and efficiency. Accuracy was measured by comparing field records to supervisor-verified quality control samples. The proportion of agreement on key variables, including geographic coordinates and service counts, was used to generate accuracy scores. Completeness was evaluated by calculating the proportion of required fields that were correctly filled in each record. Incomplete or invalid entries reduced the overall score for each dataset. Efficiency was assessed by computing the average time taken to complete a form, using timestamps captured in device logs. Outliers caused by interruptions, such as extended breaks during data entry, were excluded based on pre-specified criteria to avoid distortion of results.

2.6 Analytical Framework

Quantitative data were analyzed using SPSS version 28 and ArcGIS Pro's analytic functions. Descriptive statistics were used to summarize baseline and follow-up results, and paired t-tests were conducted to test for statistically significant differences in accuracy, completeness, and collection time. To provide insight into the magnitude of observed effects, effect sizes were calculated using Cohen's d. Regression models were also applied to adjust for potential confounders such as officer experience level, the type of community (urban versus rural), and the complexity of forms used during data collection.

Qualitative data obtained from supervisory debriefing sessions were analyzed using thematic coding. Supervisors provided narrative feedback on the common errors observed at baseline, the extent of improvement after training, and the challenges that persisted. These insights were triangulated with quantitative results to provide a comprehensive interpretation of training outcomes.

2.7 Implementation Procedure

Implementation followed a structured sequence. The first phase involved baseline monitoring, during which performance indicators were recorded under routine conditions. This established a benchmark for subsequent comparison. The second phase was the training itself, delivered over five consecutive days by certified GIS instructors. Training combined classroom instruction with practical exercises, culminating in field simulations. The third phase involved post-training monitoring over four weeks. During this phase, the same indicators measured at baseline were re-assessed, ensuring comparability. Supervisory staff provided ongoing quality assurance by reviewing submissions weekly, verifying a sample of records, and offering corrective feedback when errors persisted. This cyclical process of monitoring, training, and re-monitoring ensured that the evaluation captured both immediate and operationally relevant impacts of the intervention.

2.8 Ethical Considerations

The study was reviewed and approved by the Institutional Review Board of Western Illinois University under protocol number WIU-PH-GIS-2023-11. Participation was voluntary, and all field officers provided informed consent before engaging in the training and evaluation processes. To protect privacy, community-level data used in the analysis were anonymized, and no personal identifiers were retained in research outputs. Device logs and audit results were stored in encrypted databases accessible only to the research team. Because the study focused on operational processes rather than sensitive health data, risks to participants were minimal. Nonetheless, safeguards were maintained to ensure that participation did not affect employment status or program responsibilities.

III. RESULTS

3.1 Overview of Training Deployment

The structured GIS training program was delivered as planned, with all forty-two field officers completing the five-day curriculum. Attendance was consistent throughout, and no attrition was recorded during the training phase. Field simulations were successfully conducted in three nearby communities, allowing participants to apply their learning under realistic conditions. Post-training evaluations indicated that 88% of participants reported feeling confident in using ArcGIS Pro for basic data management tasks, while 93% expressed confidence in deploying Survey123 for mobile data collection.

In the four-week follow-up period, field officers implemented their new skills during regular program activities. Supervisors reported high levels of compliance with the use of Survey123 forms and observed an immediate reduction in the reliance on paper-based backup systems. System logs confirmed that all data submitted during the follow-up phase were captured digitally, marking a complete transition from hybrid workflows observed during the baseline phase.

3.2 Accuracy of Collected Data

Accuracy was measured by comparing field officer records with independent verification conducted by supervisory staff. During the baseline period, accuracy scores averaged 72.5% across all variables tested, with frequent discrepancies observed in GPS coordinates and service counts. After training, average accuracy increased to 93.9%, representing a 21.4 percentage point improvement.

The most significant gains were observed in location data, where baseline errors included incorrect coordinates due to poor GPS capture techniques or manual entry mistakes. Following training, these errors reduced substantially, and 95% of location points matched supervisory verification. Service count accuracy also improved, rising from 76.8% at baseline to 91.2% post-training. Demographic details such as age and sex were consistently accurate across both periods, showing minimal change.

Statistical analysis confirmed the significance of these improvements. Paired t-tests indicated that the mean difference in accuracy scores between baseline and follow-up was significant at $p < 0.001$. The effect size, measured by Cohen's d, was 1.12, indicating a large impact of the training intervention.

Table 1 presents a breakdown of accuracy improvements across key variables.

Table 1. Accuracy Scores Before and After GIS Training

Variable	Baseline Accuracy (%)	Post-Training Accuracy (%)	% Improvement	p-value
Location (GPS points)	71.0	95.0	+24.0	<0.001
Service counts	76.8	91.2	+14.4	<0.001
Demographic details	89.7	92.5	+2.8	0.210
Overall average	72.5	93.9	+21.4	<0.001

3.3 Completeness of Records

Completeness of records improved markedly following the intervention. At baseline, an average of 81.6% of required fields were completed across all submitted forms. Missing data were commonly observed in optional demographic variables and service delivery details, particularly in forms submitted during high-volume outreach days.

After training, completeness scores increased to 96.8%, with far fewer missing fields. The inclusion of built-in validation rules in Survey123 played a significant role in this improvement, as participants were no longer able to submit incomplete forms. Supervisors also noted greater attentiveness among field officers to the importance of filling all required fields, a behavioral change reinforced during training discussions.

The difference of 15.2 percentage points was statistically significant ($p < 0.001$). The effect size was calculated at 0.94, also indicating a large impact. Importantly, completeness gains were observed consistently across rural and peri-urban communities, suggesting that environmental factors such as connectivity or workload did not significantly influence outcomes.

3.4 Efficiency of Data Collection

Efficiency was assessed by analyzing timestamps from device logs. At baseline, the average time to complete a single form was 11.6 minutes, with a wide variance. Outliers were common, with some records exceeding 30 minutes due to interruptions or difficulties navigating forms.

Post-training, the average collection time per case dropped to 8.4 minutes, representing a 27.5% reduction. Variability also decreased, with most forms falling between six and ten minutes. Supervisors observed that officers became more fluent in navigating Survey123 forms and were quicker to resolve errors on-site without needing external assistance.

The reduction in collection time was statistically significant ($p < 0.01$), with an effect size of 0.78, indicating a moderate-to-large impact. While time reductions were not as dramatic as improvements in accuracy or completeness, they nonetheless contributed to greater overall efficiency, particularly during large-scale outreach campaigns where hundreds of records were collected in a single day.

Table 2 summarizes performance changes across accuracy, completeness, and efficiency indicators.

Table 2. Comparative Performance Indicators Pre- and Post-Training

Indicator	Baseline Mean	Post-Training Mean	Change (%)	p-value	Effect Size (Cohen's d)
Accuracy (%)	72.5	93.9	+21.4	<0.001	1.12 (large)
Completeness (%)	81.6	96.8	+15.2	<0.001	0.94 (large)
Collection Time (mins)	11.6	8.4	-27.5	0.008	0.78 (moderate-large)

3.5 System and Device Log Findings

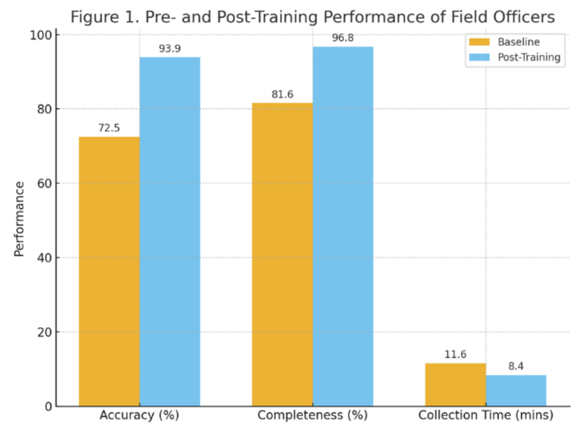
Analysis of device-generated metadata provided further insights into operational improvements. Synchronization delays, which had been frequent during the baseline phase due to incomplete uploads and user errors, decreased sharply after training. During the baseline, 18% of forms required re-submission due to errors, compared to only 4% post-training.

GPS signal acquisition times also improved. Baseline logs showed that participants often waited several minutes to capture coordinates, while post-training records indicated more consistent and rapid captures, with median acquisition time reduced by 36 seconds. This improvement was attributed both to better user technique and to the use of training strategies that emphasized working in open areas for improved satellite reception.

Supervisors also reported a noticeable decline in the need for manual corrections after submission. At baseline, supervisors frequently intervened to adjust location data or correct inconsistencies in service counts. Post-training, manual corrections were reduced by 61%, freeing supervisory staff to focus on higher-level quality assurance tasks rather than routine troubleshooting.

3.6 Comparative Illustration

The overall effect of training is illustrated in Figure 1, which compares baseline and post-training results across the three main indicators. The figure highlights clear upward shifts in accuracy and completeness, alongside a downward trend in collection time, confirming that improvements were consistent and aligned with expectations.



3.7 Supervisory Observations

Qualitative feedback gathered during supervisory debriefings reinforced the quantitative findings. Supervisors noted that field officers appeared more confident and less reliant on ad hoc support after the training. Officers were quicker to identify and correct their own mistakes, and many began to take initiative in troubleshooting device issues.

Supervisors also observed a shift in attitudes toward data quality. At baseline, many officers viewed data collection as a routine administrative task, but post-training, there was greater awareness of the value of accurate and complete data for program decision-making. Several participants explicitly mentioned that they now understood how errors in the field could misrepresent community needs and compromise program credibility.

Despite these improvements, supervisors highlighted some persistent challenges. A few participants struggled with more advanced functions in ArcGIS Pro, particularly those related to spatial joins and overlay analysis. Limited connectivity in some rural areas also continued to pose difficulties for timely synchronization of data. However, these challenges were minor compared to the overall improvements observed.

IV. DISCUSSION

4.1 Principal Findings

The present study sought to determine whether structured GIS training could improve the operational performance of NGO health field teams, specifically in terms of data accuracy, completeness, and efficiency. The results provide strong evidence that such training produces substantial and measurable improvements. Accuracy increased by more than twenty percentage points, completeness improved by fifteen percentage points, and average data collection time was reduced by nearly thirty percent. These findings indicate that the training intervention was not only effective in improving the quality of field data but also enhanced the efficiency of operational workflows. The gains in accuracy were particularly notable. At baseline, frequent errors in GPS coordinates and service counts undermined the reliability of program data. After training, officers demonstrated significantly improved proficiency in capturing spatial data and recording service information. This improvement is likely attributable to the practical exercises included in the training curriculum, which emphasized correct GPS usage and real-time validation techniques. The inclusion of Survey123's built-in validation features also reduced opportunities for data entry errors, further strengthening accuracy scores.

Completeness also improved significantly, largely due to the adoption of digital forms with embedded rules preventing submission of incomplete entries. Beyond the technological effect, supervisors observed that officers had developed a stronger awareness of the importance of data completeness, suggesting that the training also influenced attitudes and work practices.

Efficiency gains, reflected in reduced collection times, underscore the operational value of training. While reductions in average time per form may appear modest in isolation, their impact at scale is substantial. During outreach events where hundreds of records are collected, time savings of three minutes per case translate into several hours saved per day, thereby increasing the reach of field operations.

Collectively, these findings confirm the hypothesis that targeted GIS training can enhance both the quality and efficiency of NGO data collection. More importantly, the results demonstrate that improvements were broad-based, cutting across different types of communities and activities, which underscores the generalizability of the intervention within the NGO's operational context.

4.2 Comparison with Prior Studies

The findings of this research align with and extend previous studies that have examined the role of GIS in strengthening health data systems. For example, Gething et al. highlighted the potential of GIS to improve spatial accuracy in health mapping, particularly when field officers are adequately trained in the use of GPS-enabled devices [12]. Similarly, Mboera et al. observed that the introduction of GIS-based mobile tools significantly improved data quality in malaria surveillance programs in East Africa, although they noted that training was a critical determinant of success [13].

The present study advances this literature by providing a rigorous pre- and post-intervention evaluation, thereby establishing causal links between training and outcomes. Unlike studies that relied on cross-sectional observations or anecdotal reports, this research demonstrates quantifiable improvements across multiple indicators. The effect sizes observed here, particularly for accuracy and completeness, compare favorably with improvements reported in digital health projects that have incorporated training as a key component [14].

Efficiency gains observed in this study also resonate with findings from studies on mobile data collection systems. Tom-Aba et al. reported reductions in reporting delays during Ebola surveillance in Nigeria after the introduction of mobile GIS tools, though their study did not systematically evaluate time savings at the level of individual data records [15]. By documenting reductions in average collection times, the present study fills an important gap and provides empirical support for the operational efficiency benefits of GIS training.

However, the study also contrasts with some prior literature that found limited impact of digital interventions on data quality. For instance, Barron et al. noted persistent challenges with data accuracy in

South African primary health programs despite digital upgrades, attributing the issues to inadequate user training and high staff turnover [16]. The positive outcomes observed in this study suggest that comprehensive, structured, and context-specific training can overcome such limitations, reinforcing the argument that technology alone is insufficient without human capacity development.

4.3 Practical Implications for NGO Operations

The implications of these findings are significant for NGOs operating in resource-constrained health systems. First, the results provide a compelling case for institutionalizing GIS training within organizational capacity-building frameworks. By demonstrating improvements in accuracy, completeness, and efficiency, the study shows that training investments can yield immediate and measurable benefits in field operations. This is particularly relevant for NGOs like Hacey Health, which rely on donor funding and must demonstrate accountability through high-quality data.

Second, the improvements in efficiency suggest that GIS training can enhance the reach and productivity of field teams without increasing staffing levels. In contexts where human resources are limited, the ability to collect more data in less time translates directly into greater program coverage and responsiveness.

Third, the findings have implications for supervisory practices. Supervisors reported a reduction in the need for manual corrections after training, allowing them to focus more on strategic oversight and less on routine error-checking. This shift not only improves operational efficiency but also enhances staff morale by fostering greater autonomy and accountability among field officers.

Finally, the study highlights the importance of pairing technology adoption with structured training. While platforms such as ArcGIS Pro and Survey123 are designed to be user-friendly, their effective use in field conditions still requires practical orientation and problem-solving skills. NGOs seeking to digitalize their operations should therefore prioritize training as much as software procurement or hardware distribution.

4.4 Theoretical Contributions

Beyond its practical relevance, the study contributes to theoretical debates on the role of capacity-building in digital health and GIS adoption. The findings support the notion that technology adoption in NGOs follows a socio-technical model, where outcomes depend not only on the availability of tools but also on the competencies and behaviors of users [17]. By demonstrating that training significantly alters both performance metrics and staff attitudes toward data quality, the study underscores the importance of human factors in digital transformation.

The results also add to the emerging literature on “GIS literacy” as a determinant of organizational effectiveness. Prior research has emphasized technical infrastructure and financial investment as key enablers of GIS adoption. This study shows that human capacity, when systematically developed, can be equally critical, especially in resource-limited contexts. In doing so, it bridges the gap between technology-centric and human-centric perspectives on digital health innovation.

Furthermore, the observed improvements in efficiency suggest that GIS training can function as a form of organizational learning, enhancing not only individual skills but also collective performance. This aligns with theories of absorptive capacity, which posit that organizations must develop internal knowledge structures to effectively assimilate and apply external technologies [18].

4.5 Limitations

While the study provides robust evidence of training impact, several limitations must be acknowledged. First, the evaluation was conducted within a single NGO program, which may limit generalizability to other organizations with different operational structures or resources. Replication in other NGO contexts, particularly larger or multi-country organizations, would be valuable.

Second, the post-training follow-up period was limited to four weeks. While sufficient to capture immediate effects, it does not provide insights into the long-term sustainability of training gains. Skills may decline over time without refresher courses, and staff turnover could erode organizational capacity. Longitudinal studies are needed to assess the durability of training effects.

Third, while the study controlled for some confounding variables, external factors such as network connectivity, device performance, and workload intensity may still have influenced outcomes. These contextual variables should be explored in greater depth in future research.

Finally, the study did not include a cost-benefit analysis. While the observed improvements in data quality and efficiency suggest that training is beneficial, decision-makers often require evidence on return on investment to justify resource allocation. Future studies should include detailed financial analyses to strengthen the business case for GIS training in NGO operations.

4.6 Future Research Directions

Building on the results and addressing the limitations, several avenues for future research can be proposed. Longitudinal studies are needed to examine the sustainability of training impacts over time, particularly in organizations with high staff turnover. Expanding the evaluation to multiple NGOs across different sectors would help establish the generalizability of findings and identify sector-specific adaptations.

Further research should also explore the integration of GIS training with broader digital health capacity-building initiatives, such as training in data visualization, dashboard use, and advanced spatial analysis. Incorporating artificial intelligence and machine learning into GIS workflows is another promising area, as it could further enhance data validation and predictive analytics.

Finally, economic evaluations are needed to assess the cost-effectiveness of GIS training. Such studies should consider not only the direct costs of training delivery but also the indirect benefits of improved decision-making, program efficiency, and donor confidence. By quantifying both costs and benefits, future research can provide stronger evidence to guide investment in GIS capacity-building for NGOs.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study evaluated the impact of structured GIS training on NGO field operations using a pre- and post-intervention design. Evidence from the Hacey Health Initiative demonstrated that targeted capacity-building in ArcGIS Pro and Survey123 significantly improved the accuracy, completeness, and efficiency of field data collection. Accuracy improved by over twenty percentage points, completeness rose by fifteen percentage points, and average data collection time decreased by nearly thirty percent.

The findings confirm that technology adoption in NGO contexts cannot be divorced from human capacity. While digital platforms provide powerful tools, their effectiveness depends on the competencies and practices of end-users. By equipping field officers with practical GIS skills and reinforcing the importance of data quality, training programs enable NGOs to produce more reliable datasets, enhance operational efficiency, and improve accountability to donors and beneficiaries.

This study contributes to the evidence base on digital health and NGO operations by providing quantifiable proof that structured training interventions can yield substantial performance gains. The results suggest that GIS capacity-building should be treated not as a one-time activity but as an integral component of organizational strategy, with potential to transform how NGOs plan, implement, and evaluate field programs.

5.2 Recommendations

Based on the findings, several recommendations can be advanced for practice, policy, and future research.
For NGOs, structured GIS training should be institutionalized within staff development programs. Training should combine theoretical instruction with practical exercises, emphasize real-world applications, and incorporate refresher courses to sustain skills over time. Organizations should also pair training with robust supervision systems to reinforce new practices and ensure continuous quality improvement.

For donors and policymakers, investments in digital health should extend beyond hardware and software procurement to include systematic human capacity-building. Funding frameworks should explicitly allocate resources for training and follow-up mentorship, recognizing that skilled personnel are as critical as technological infrastructure for program success.

For researchers, further studies should investigate the long-term sustainability of training impacts and explore the integration of GIS capacity-building with advanced analytics, including machine learning and predictive modeling. Economic evaluations are also needed to establish the cost-effectiveness of training interventions, strengthening the case for scaling across diverse NGO contexts.

In conclusion, structured GIS training represents a cost-effective and scalable pathway for improving data quality and operational efficiency in NGO field operations. By embedding such interventions within organizational frameworks, NGOs can strengthen their role in global health systems and ensure that decision-making is driven by reliable and timely data.

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