Journal of Health Informatics in Africa

9th Health Informatics in Africa Conference (HELINA 2014)
Peer-reviewed and selected under the responsibility of the Scientific Programme Committee

Mobile-health tool use and community health worker performance in the Kenyan context: a quasi-experimental post-test perspective

Maradona Gatara [a,*], Jason F Cohen [b]

[a] University of the Witwatersrand, Johannesburg, South Africa
[b] University of the Witwatersrand, Johannesburg, South Africa

Background and Purpose: Community Health Workers (CHW's) are often the only link to healthcare for millions of people in the developing world. Mobile-health or 'mHealth' tools can support CHWs in monitoring and evaluation, disease surveillance, and point-of-care diagnostics. However, there is a lack of evidence on the impacts of mHealth on CHW performance. To address this gap, we determine a set of measures along which to evaluate the impact of mHealth tools on CHW performance.
Methods: Using a quasi-experimental post-test design we compare CHWs using an mHealth tool (n=196) with those using a paper-based system (n=199). The empirical context for the study is peri-urban communities in Kenya and data was collected using a survey instrument.
Results: Results provide evidence of impacts of mHealth tool use on objective and perceptual performance measures.
Conclusions: CHWs using mHealth tools capture and transmit higher percentages of monthly cases on time and without missing data, and are highly satisfied with the contribution of the tool to their performance.

Keywords: mHealth, Community Health Workers (CHWs), Performance

1 Introduction

Community Health Workers or CHW's are often the only link to healthcare for millions of people in the developing world. They contribute by conducting monitoring and evaluation exercises and disease surveillance, and providing point-of-care diagnostic support [2, 24]. CHW's also link households in their communities to skilled healthcare practitioners in clinics and hospitals – for the treatment of complicated illnesses or specialized maternal care [2]. As a consequence, supporting CHW's at the point-of-care is thus of significant importance. One-way to achieve this is through the application of mobile-health or 'mHealth' technologies [2, 3]. These platforms offer the promise of improving CHW performance by facilitating the capture, storage, transmission and retrieval of health data – whilst representing the most immediate and cost effective way to save lives and improve care in low-resourced community settings [4]. Unfortunately, mHealth initiatives are often unsustainable pilot projects that not only fail to 'scale-up' meaningfully, but also expire once initial funding is exhausted. For example, between 2008 and 2009, 23 mHealth initiatives were introduced in Uganda, yet none 'scaled-up' beyond the pilot phase. Similarly, in 2009, despite the launch of over 30 mHealth initiatives in India, none were fully deployed to scale [4]. This is exacerbated by a lack of substantive evidence regarding the impacts of mHealth tools on healthcare service delivery and CHW performance [2, 4]. The purpose of this paper is to address this gap. More specifically, this paper aims to (a) determine a relevant set of measures along which to evaluate the impact of mHealth tools on CHW performance, and (b) use these measures to compare CHW's in mHealth technology-enabled and paper-based system settings. The study employs a quasi-experimental

*Corresponding author address: 1 Jan Smuts Avenue, Braamfontein, 2000. Email: mcgatara@gmail.com, maradonagatara@gmail.com Tel: +27793204215
 DOI: 10.12856/JHIA-2014-v2-i2-108

post-test-only design [5, 6, 7, 8] to compare a group of CHW's using an mHealth tool (see Figure 1), to a reference group using a traditional paper-based tool – where the empirical context for the study is peri-urban communities in Kenya. This comparison would provide much needed evidence of mHealth impacts on CHW performance. In order to be an effective link between their communities and the broader healthcare system (including hospitals and clinics) - CHW's have to do a reliable job of capturing health data and reporting on typical tasks of monitoring, health promotion, and referral that they perform. It is therefore important to evaluate the extent to which mHealth can be associated with improved task performance and enhanced reporting.

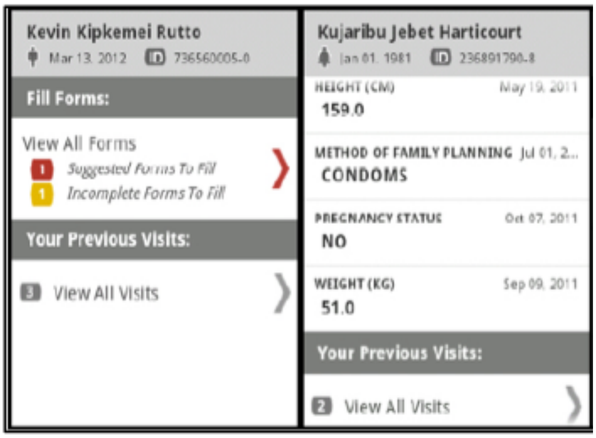

Figure 1. Monitoring task interface for 'OpenMRS' compatible mHealth tool used in Nandi County (one of the study sites)

There has been sustained interest in understanding the impacts of Information Technologies (IT's) on individual user performance [9]. Various studies use self-reported, often perceptual indicators of individual performance in the accomplishment of tasks – whereby higher performance implies a mix of improved efficiency, effectiveness, and higher quality [9, 10, 11, 12, 13, 14]. These dimensions of individual performance can be understood as follows. Firstly, *effectiveness* is the individual's completion or accomplishment of tasks and includes the speed with which the tasks are performed [9, 12]. The availability of advanced information technologies is often associated with improvements in effectiveness by aiding the timeliness of output produced [15] - in addition to providing information in a format that easily allows for reliable decision support. Secondly, *efficiency* is the time taken to complete tasks using minimal resources or the extent to which an individual does more work in the least amount of time and at lower cost [9]. Advanced information technologies are expected to improve user efficiency by enabling or limiting work activities [15], by automating time-consuming tasks or reducing wastage of available resources. Thirdly, *quality* is the extent to which an individual performs a task or set of tasks, whilst committing minimal errors, with improved decision making yielding better output [9, 11, 12]. The availability of advanced information technologies is expected to enhance the quality of information [15] by allowing for improved data validation and thus reducing or preventing errors. To capture such performance, many past studies e.g. [16, 17, 18] have used self-reported perceptual measures, with items such as 'the system has improved my productivity'. In addition to these perceptual aspects of performance, a number of more objective indicators also exist in the CHW context [19]. These encompass measures similar to workload (number of reported monthly cases), throughput (% of households visited monthly), flow time (hours taken to complete case reports weekly), and error rate (% of reports returned to sender due to errors or inconsistencies). Thus both perceptual and objective measures can usefully be included in a study of mHealth tool impacts on CHW performance. The study design used to compare the individual performance of mHealth tools users to paper-based tool users is presented next.

2 Materials and methods

To address the study's objective of comparing performance of CHWs operating in mHealth versus paper-based settings, a quasi-experimental post-test-only design was used [5, 6, 8]. More specifically, an intervention (X), namely the use of an mHealth tool, has been implemented for one group of CHW's but

 DOI: 10.12856/JHIA-2014-v2-i2-108

not for a second control group [5]. If performance (O) were compared across both groups, then (O1) would be individuals' performance in the mHealth tool user group after the intervention, and (O2) would be individuals' performance in the paper-based tool user group. This relationship is expressed in the following formula:

$$\frac{\textit{Interventiongroup (mHealth Tool Users): X 01}}{\textit{Controlgroup (Paper-Based Tool Users): O2}}$$

This design allows us to evaluate the differences in performance between the intervention group comprising users of mHealth tools, and the control group made up of users of paper-based tools. The use of this quasi-experimental design was necessary because in this scenario, the researchers had no control over the introduction of the intervention, and random assignment of CHWs to either the intervention or control groups was not possible. Moreover, since the intervention was already in progress at the time of the study, it was also not possible to carry out a pre-test to ensure equivalence at baseline [7]. Consequently, the study relied on a post-test-only design [5]. A cross-sectional survey design was used to collect data from CHWs in each of the two groups. A structured questionnaire was developed as the research instrument of choice [20, 21]. For the intervention group (X O1), data was obtained from CHWs using an mHealth tool operating within peri-urban communities in the counties of Siaya, Nandi, and Kilifi in Kenya. For the control group (O2), data was obtained from CHWs using a paper-based reporting system operating within peri-urban communities in the counties of Nairobi and Nakuru in Kenya. A proportionate stratified sampling approach with systematic random sampling [22] was used to construct the sampling frame. Specifically, within each county, 'k' number of Community Health Units (CHU's) comprising CHW's was identified, and a proportional number of CHW's systematically drawn from lists of CHW's operating in each unit. The number drawn represented the sampling frame for each county. **Figure 2** illustrates the sampling approach followed.

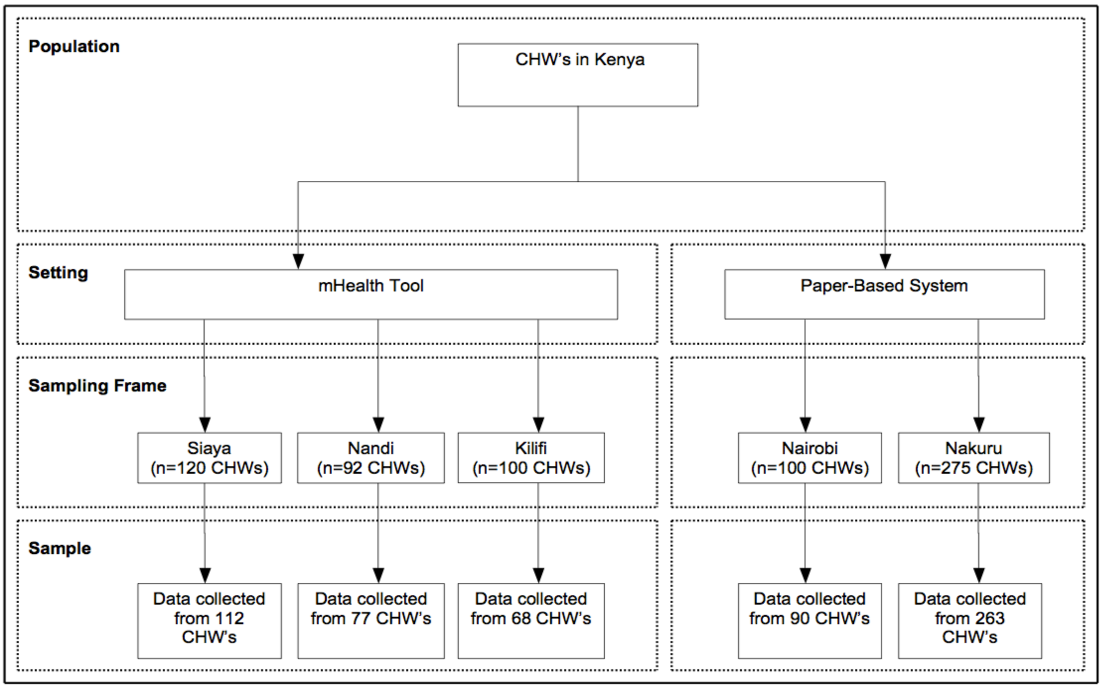

Figure 2. Sample design

In order to ensure content validity i.e. the extent to which items fully reflected the concepts being measured [23], the survey instrument was firstly, developed from literature and secondly, administered to eight experts - four academics (two Information Systems (IS) scholars and two social scientists), and four healthcare service practitioners (one community health service expert and three health service field officers) – all asked to scrutinize it and give an informed opinion about the item measures [7]. To ensure face validity [7], the survey instrument was administered in a pilot study involving thirteen CHW's from

 DOI: 10.12856/JHIA-2014-v2-i2-108

the mHealth tool user group and 15 CHW's from the paper-based tool user group. Their recommendations were incorporated into the instrument. For individual performance, the variables along which we describe and compare these two user groups are both perceptual and objective measures that are relevant to the context of CHW work. Eight items were used to capture the perceived impacts of the respective tool (mHealth or paper-based) on the effectiveness, quality, and efficiency of the CHW. Items 1, 4, 5, and 7 were drawn from [18] measuring effectiveness, quality, and efficiency, as aspects of task productivity as a perceived impact of Information Technology (IT) use. Items 2, 3, and 8 were drawn from [17], who also used these to measure effectiveness and quality, whereas item 6, drawn from [16], provided an additional measure of task effectiveness.

To ensure construct validity, these individual performance measures were drawn from prior validated instruments [21]. There were eleven objective performance measures – including reporting on various quantities of work, as well as percentages affecting task completion and error rates. These measures covered CHW workload (number of reported monthly cases), throughput (% of households visited monthly), and flow time (hours taken to complete case reports weekly) to provide measures of effectiveness in tool reporting. CHW error rate (% of reports returned to sender due to errors or inconsistencies) and completeness of reporting (% of complete monthly reports) provided measures of quality of reporting.

These measures were deemed most relevant following discussions held in the field with community health specialists, coordinators, extension workers (2 to 4 in each county), and a handful of experienced CHW's. Various documents also supported selection of these performance indicators, including policy reports on health worker performance assessment frameworks, monthly performance evaluation checklists, and Community Health Extension Worker (CHEW) summary indicators. District level support supervision checklists from the Ministry of Health (MOH) - Division of Community Health Services (DCHS), community strategy manuals, and MOH registers used by CHW's for reporting were also reviewed. Some of these indicators are conceptually similar and comparable to those employed in health studies by [19], [20], [25], and [26], yet adapted and contextualized for this study. The survey instrument also elicited demographic data, namely – age, gender, education level, experience as a CHW (in years), and tool (mHealth or paper-based) use experience (in months). **Table 1** shows the survey instrument items used to measure perceptual and objective CHW performance.

3 Results

3.1 Response Rate and Sample Profile

The survey instrument was administered to 687 respondents – 312 in the intervention group comprising mHealth tool users (O1), and 375 in the control group (O2) comprising paper-based tool users. For O1, 257 responses were received from mHealth tool users, yielding an 82% response rate. For O2, 353 responses were received from paper-based tools users, for a 94% response rate. The data obtained from respondents was screened for missing values and outliers using multivariate methods [27]. Cases with large amounts of missing data or those with consistently extreme response sets were deleted. This resulted in the exclusion of 52 responses from the mHealth tool user group and 136 from the paper-based tool user group. Consequently, 205 usable responses for the mHealth tool user group, and 217 usable responses for the paper-based tool user group were retained for analysis. The large number of missing responses was not unexpected given conditions in the field setting in which the instrument was administered. Table 2 shows that across the two user groups, most respondents were relatively young. Amongst mHealth tool users, the majority reported ages between 25 and 34 years (50%). Although a fairly similar trend was followed amongst paper-based tool users (36%), there was however a statistically significant difference in age between the two groups (U = 18418.500, p < 0.001). Specifically, there were proportionately more respondents aged 45 years and older in the paper-based tool user group. Male and female users across the two groups did not differ significantly: χ^2 = 0.294, p = .588. In both groups, there are more female (62% use mHealth tools and 65% use paper-based tools) than male (38% use mHealth tools and 35% use paper-based tools) users. A Kruskal-Wallis test [28] showed users' education levels did not differ significantly across the two groups: χ^2 = 0.239, p = .625. Most mHealth tool users have attained secondary level education (74%). This is also evident for paper-based tool users, with most respondents (77%) educated up to secondary school level. Similarly, there was no statistically significant difference in tool use

 DOI: 10.12856/JHIA-2014-v2-i2-108

experience across the groups: $\chi^2 = 0.002$, $p = .965$. Amongst mHealth tool users, most reported tool use for five or more months (79%). Most paper-based tool users reported similar levels of tool use experience (78%). Although, paper-based tool users had more years of experience as CHW's (median = 3.50) than mHealth tool users (median = 3.00 years), this difference was not statistically significant ($p = .484$). Significant differences were thus found only in relation to age, whilst none were found with respect to gender, experience as a CHW, education level, and tool use experience – thus establishing areas of non-equivalence at baseline [29], controlled for in subsequent analyses. Given the low number of respondents having 'Less Than 1 Month' and '1-2 Months' of tool use experience, it was decided to omit them from further analyses, and only those with '3-4 Months' and '5 or More Months' were retained. The relationship between the objective user performance indicators and these relatively more experienced tool users within each setting, i.e. mHealth (n=196) and paper-based (n=199) tool use is discussed in the next section.

Table 1. CHW Performance Indicators

			Dimension		
No	**Item**	**Measure**	**Effectiveness**	**Efficiency**	**Quality**
User Perceptions					
PUP1	The mHealth / paper-based tool makes me more productive.	Perceptual	✓		
PUP2	The mHealth / paper-based tool makes me more effective with patients.	Perceptual	✓		
PUP3	The mHealth / paper-based tool improves my quality of patient care.	Perceptual			✓
PUP4	The mHealth / paper-based tool helps me save time.	Perceptual		✓	
PUP5	The mHealth / paper-based tool helps me finish my tasks more quickly.	Perceptual	✓		
PUP6	Using the mHealth / paper-based tool improves my effectiveness in performing tasks.	Perceptual	✓		
PUP7	The mHealth / paper-based tool improves the quality of my task performance.	Perceptual			✓
PUP8	The mHealth / paper-based tool helps me make fewer errors in reporting.	Perceptual			✓
Health Data Capture and Transmission					
OUP1	How many households do you visit per month?	Objective	✓		
OUP2	What percentage of the households visited are you able to report?	Objective	✓		
OUP3	Of the households visited, how many monitoring cases do you report per month?	Objective	✓		
OUP4	Of the households visited, how many health promotion cases do you report per month?	Objective	✓		
OUP5	Of the households visited, how many referral cases do you report per month?	Objective	✓		
OUP6	In a typical week, how much time (in hours) do you take to complete reports for monitoring cases?	Objective		✓	
OUP7	In a typical week, how much time (in hours) do you take to complete reports for health promotion cases?	Objective		✓	
OUP8	In a typical week, how much time (in hours) do you take to complete reports for referral cases?	Objective		✓	
OUP9	Of the cases reported per month, approximately what percentage are completed on time?	Objective	✓		
OUP10	Of the reports completed for all cases per month, what percentage are complete (i.e. no missing data)?	Objective			✓
OUP11	What percentage of the reports completed are returned to you for additional information due to errors or inconsistencies?	Objective			✓

3.2 The Influence of Setting on Objective CHW Performance

Analysis of Covariance (ANCOVA) was effected to compare the two groups of tool users (mHealth versus paper-based) along the eleven objective performance indicators. We controlled for demographics including age, gender, experience as a CHW, education level, and tool use experience. Significant differences across the groups were found for only two of the eleven objective performance measures, i.e.

 DOI: 10.12856/JHIA-2014-v2-i2-108

OUP9 (percentage of monthly cases reported on time), and OUP10 (percentage of complete monthly cases reported). No significant differences were found for the nine remaining objective user performance indicators. However, education level, tool use experience, and experience as a CHW, were found to have effects on six of the eleven objective performance measures, i.e. OUP1 (monthly household visitations), OUP2 (percentage of monthly household visitations), OUP4 (monthly health promotion cases reported), OUP9 (percentage of reported monthly cases reported on time), OUP10 (percentage of complete monthly cases reported), and OUP11 (percentage of reports completed with no errors or inconsistencies). **Table 2** shows the differences in tool use setting and objective performance.

Figure 3 shows percentages of reports completed on time for mHealth versus paper-based tool users (OUP9). While 12% of mHealth tool users were able to report 90-100% of cases on time, only 4% of paper-based tool users were able to do the same. Moreover, 37% of mHealth tool users reported more than 60% of cases on time, whilst only 27% of paper based tool users managed the same. This impact of mHealth use on OUP9 is significant (F=16.546, p< 0.001).

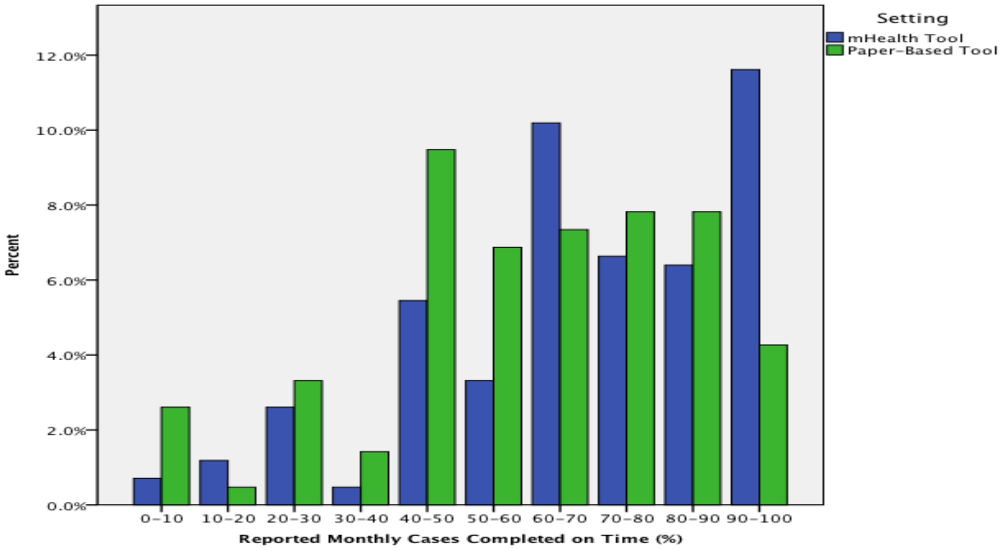

Figure 3. Differences in reported monthly cases completed on time

In addition to the effects of the tool itself, tool use experience was also found to have an effect on OUP9, where F (1, 357) = 20.33, p = 0.000, partial η^2 = .994. This effect is depicted in **Figure 4**, which illustrates a plot of the interaction between tool use experience and setting along performance indicator OUP9.

 DOI: 10.12856/JHIA-2014-v2-i2-108

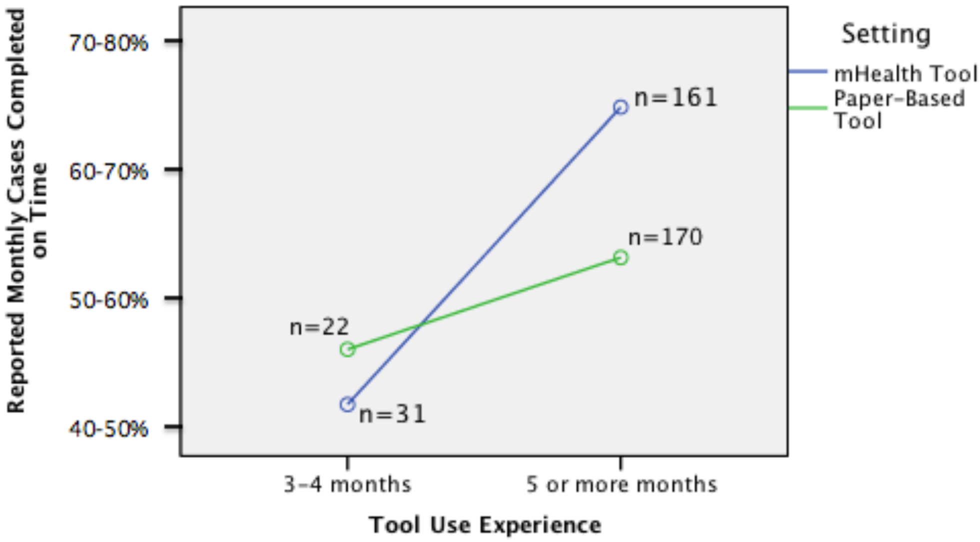

Figure 4. Effect of tool use experience on monthly household visitations reported

 DOI: 10.12856/JHIA-2014-v2-i2-108

Table 2. Differences in setting and objective user performance

		F-ratio	Sig (p)	Partial η^2
Setting Significant				
OUP9.	Of the cases reported per month, approximately what percentage is completed on time?	16.546	0.000***	.982
Tool Use Experience was found to have an effect on OUP9, where F (1, 357) = 20.33, p = 0.000***, partial η^2 = .994.				
OUP10.	Of the reports completed for all cases per month, what percentage is complete (i.e. no missing data)?	10.104	0.002*	.887
Tool Use Experience was found to have an effect on OUP10, where F (1, 357) = 12.02, p = 0.001*, partial η^2 = .933.				
Setting Not Significant				
OUP1	How many households do you visit per month?	0.001	0.975	0.050
Education Level was found to have an effect on OUP1, where F (1, 357) = 9.77, p = 0.002*, partial η^2 = .876				
OUP2	What percentage of the households visited are you able to report?	2.747	0.098	.380
Tool Use Experience was found to have an effect on OUP2, where F (1, 357) = 11.94, p = 0.001*, partial η^2 = .931.				
OUP3	Of the households visited, how many monitoring cases do you report per month?	0.138	0.711	0.066
OUP4	Of the households visited, how many health promotion cases do you report per month?	3.187	0.076	0.428
Experience as a CHW was found to have an effect on OUP4, where F (1, 357) = 8.76, p = 0.003*, partial η^2 = .838.				
OUP5	Of the households visited, how many referral cases do you report per month?	0.473	0.493	0.105
OUP6	In a typical week, how much time (in hours) do you take to complete reports for monitoring cases?	0.206	0.650	0.074
OUP7	In a typical week, how much time (in hours) do you take to complete reports for health promotion cases?	0.896	0.345	0.157
OUP8	In a typical week, how much time (in hours) do you take to complete reports for referral cases?	1.243	0.266	0.199
OUP11	What percentage of the reports completed are returned to you for additional information due to errors or inconsistencies?	0.339	0.561	0.089
Tool Use Experience was found to have an effect on OUP11, where F (1, 357) = 5.95, p = 0.015*, partial η^2 = .682				

*** p<0.0001 **p<0.01 *p<0.05

In the early months of use, mHealth tool users reported fewer monthly cases completed on time compared to paper-based tool users. However, after five or more months of use, mHealth tool users reported significantly higher percentages than paper-based tool users.

3.3 Perceptual User Performance Differences

A descriptive comparison of mHealth and paper-based tool users along the 8 perceptual performance indicators (PUP1 – PUP8) was also carried out. **Figure 5** shows the means and confidence intervals for the two groups, where users show generally higher positive perceptions of mHealth tool use compared to paper-based tool use. Across all 8 measures, mHealth tool users report greater satisfaction with the tool's performance impacts. Moreover, confidence intervals do not overlap, thus providing support for the perceived effect of mHealth tool use on performance. Users of mHealth tools are clearly more satisfied on average with the contribution of the tool to their performance. This satisfaction is important in a context

 DOI: 10.12856/JHIA-2014-v2-i2-108

such as this, having been shown in past work to critically determine success related to use of information systems [30, 31, 32, 16] the belief that systems meet users information requirements [33], or the affective attitude of users as they interact with systems [30].

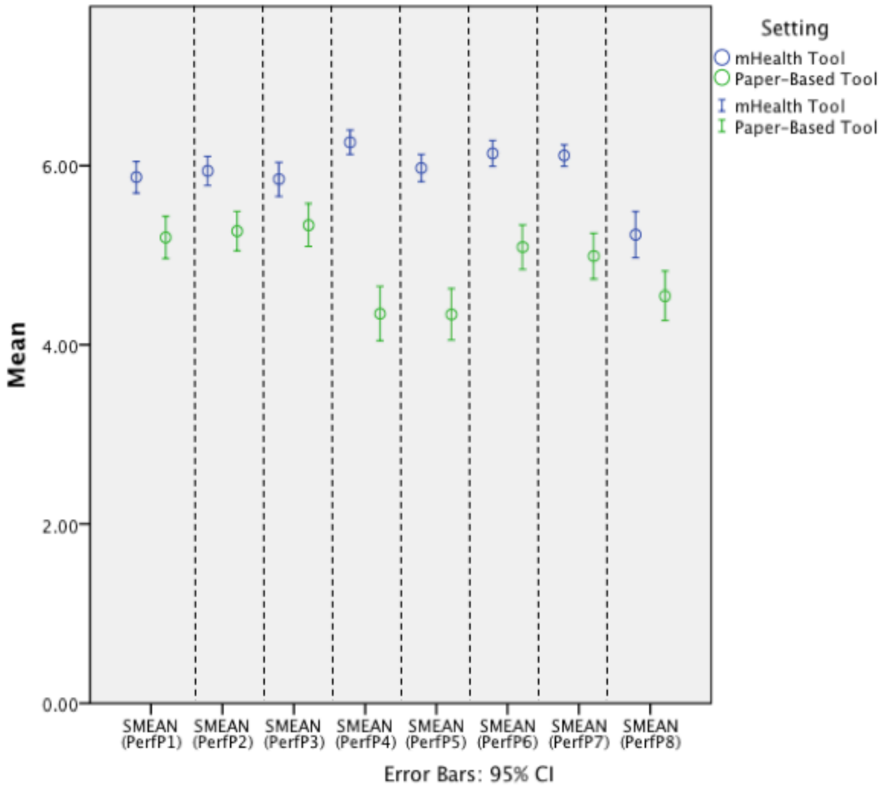

Figure 5. Perceptual Performance means with 95% confidence intervals

4 Discussion

Users of the mHealth tool have shown higher levels of satisfaction with the tool's contribution to performance than paper-based tool users across all perceptual indicators examined. By using mHealth tools, CHW's also achieve superior performance along more objective indicators, which reflect enhanced levels of reporting of healthcare service tasks. In particular, they report higher percentages of monthly cases on time and without missing data. In addition, findings also suggest that mHealth tool users may initially be more sluggish with use than their paper-based counterparts, but eventually gain enough experience with the mHealth tool to report higher percentages of monthly cases completed on time. Initial productivity dips at the early stages of an IT intervention are not uncommon, given that users need time to adapt to a particular tool use setting before performance benefits are fully realized [15]. This study's results provide much needed evidence of mHealth impacts on CHW performance outcomes. Our results are generally positive that mHealth can assist health workers to better serve their communities and link them with the broader healthcare system.

Acknowledgements

We sincerely thank the Ministry of Health (MOH) Division of Community Health Services (DCHS) and all Community Health Workers (CHWs) who participated in the study.

 DOI: 10.12856/JHIA-2014-v2-i2-108

References

[1] Mechael P, The Case for mHealth in Developing Countries. Innovations. 2009; 4(1):103-18.

[2] One Million Community Health Workers: Technical Taskforce Report. Earth Institute [Internet]; 2010 [cited 2015 Feb 24]. Available from http://milleniumvillages.org/uploads/ReportPaper/1mCHW_TechnicalTaskForceReport.pdf

[3] Liu A, Sullivan S, Khan, M, Sachs S, Singh P. Community Health Workers in Global Health. Scale and Scalability. Mt Sinai J Med. 2011; 78(1):419-35.

[4] LeMaire J. Scaling Up Mobile Health: Elements for the Successful Scale Up of mHealth in Developing Countries. Geneva: Advanced Development for Africa [Internet]; 2011 [cited 2015 Feb 24]. Available from http://www.k4health.org/sites/default/files/ADA_mHealth%20White%20Paper.pdf

[5] Harris A, McGregor J, Perencevich E, Furino J, Zhu J, Peterson J, et al. The Use and Interpretation of Quasi-Experimental Studies in Medical Informatics. J Am Med Inform Assoc. 2006; 13(1):16-23.

[6] Cook T, Shadish W, Wong V. Three Conditions Under Which Experiments and Observational Studies Produce Comparable Causal Estimates: New Findings from Within-Study Comparisons. J Policy Anal Manage. 2006; 27(4):724-50.

[7] Leedy P, Ormrod, J. Practical Research: Planning and Design. New Jersey: Pearson; 2013.

[8] Creswell J. Research Design. Qualitative, Quantitative, and Mixed Method Approaches. California: Sage Publications; 2014.

[9] Goodhue D, Thompson R. Task-Technology Fit and Individual Performance. MIS Quarterly. 1995; 19(2):213-36.

[10] Goodhue, D. The Model Underlying the Measurement of the Impacts of the IIC on the End Users. J Am Soc Inf Sci. 1997; 48(5):449-53.

[11] D'Ambra J, Wilson C. Use of the World Wide Web for International Travel: Integrating the Construct of Uncertainly in Information Seeking and the Task-Technology Fit (TTF) Model. J Am Soc Inf Sci Technol. 2004; 55(8):731-42.

[12] Teo S, Men B. Knowledge Portals in Chinese Consulting Firms: A Task-Technology Fit Perspective. European Journal of Information Systems. 2008; 17(1):557-74.

[13] Cane S, McCarthy R. Analyzing the Factors that Affect Information Systems Use: A Task-Technology Fit Meta-Analysis. Journal of Computer Information Systems. 2009:108-23.

[14] D'Ambra J, Wilson C, Akter, S. Application of the Task-Technology Fit Model to Structure and Evaluate the Adoption of E-Books by Academics. J Am Soc Inf Sci Technol. 2013; 64(1):48-64.

[15] Belanger F, Collins R, Cheney P. Technology Requirements and Work Group Communication for Telecommuters. Information Systems Research. 2001; 12(2):155-76.

[16] Hou C. Examining the Effects of User Satisfaction on System Usage and Individual Performance with Business Intelligence Systems: An Empirical Study of Taiwan's Electronics Industry. Int J Inf Manage. 2012; 32(6):560-73.

[17] Junglas I, Abraham C, Ives B. Mobile Technology at the Frontlines of Patient Care: Understanding Fit and Human Drives in Utilization Decisions and Performance. 2009; 46(3): 534-647.

[18] Torkzadeh G, Doll W. The Development of a Tool for Measuring the Perceived Impact of Information Technology on Work. The International Journal of Management Science. 1999; 27(1):327-39.

[19] Arango J, Iyengar M, Dunn K. Performance Factors of Mobile Rich Media Job Aids for Community Health Workers. J Am Med Inform Assoc. 2011; 18(1):131-37.

[20] Hair J, Babin B, Money A, Samouel, P. Essentials of Business Research Methods. Chichester: Wiley; 2003.

[21] Saunders M, Lewis P, Thornhill A. Research Methods for Business Students. Edinburgh Gate, Harlow: Pearson; 2012.

[22] Daniel J. Sampling Essentials: Practical Guidelines For Making Sampling Choices. California: Sage; 2012.

[23] Vanderstoep S, Johnston D. Research Methods For Everyday Life, Blending Qualitative and Quantitative Approaches, California: Jossey-Bass, San Francisco; 2009.

[24] Gopalan S, Mohanty S. Assessing Community Health Workers Performance Motivation: A Mixed-Methods Approach on India's Accredited Social Health Activists (ASHA) Programme. BMJ Open. 2012; 2(5):1-11.

[25] Ndedda C, Wamae A, Ndirangu, M, Wamalwa D, Wangalwa G, Watako P, et al. Effects of Selected Socio-Demographic Characteristics of Community Health Workers on Performance of Home Visits During Pregnancy: A Cross-Sectional Study in Busia District, Kenya. Glob J Health Sci. 2012; 4(5):78-90.

[26] Kruk M, Freedman L. Assessing Health System Performance in Developing Countries: A Review of the Literature. Health Policy. 2008; 85(1):263-76.

[27] Hair J, Black W, Babin B, and Anderson R. Multivariate Data Analysis. New Jersey: Prentice Hall; 2010.

[28] Brace N, Kemp R, Snelgar R. SPSS for Psychologists. Hampshire: Palgrave Macmillan; 2012.

[29] Ruland C. Handheld Technology to Improve Patient Care. J Am Med Inform Assoc. 2002; 9(2):192-201.

 DOI: 10.12856/JHIA-2014-v2-i2-108

[30] Doll W, Torkzadeh G. The Measurement of End-User Computing Satisfaction. MIS Quarterly. 1988; 12(2): 1151-71.
[31] Igbaria M, Tan M. The Consequences of Information Technology Acceptance on Subsequent Individual Performance. Information and Management. 1997; 32(3):113-21.
[32] Ives B, Olson M, Baroudi J. The Measurement of User Information Satisfaction. Commun ACM. 1983; 26(10):785-793.
[33] DeLone W, McLean E. Information Systems Success: The Quest for the Dependent Variable. Information Systems Research. 1992; 3(1):60-95.

 DOI: 10.12856/JHIA-2014-v2-i2-108