Matching Task and Technology Characteristics to Predict mHealth Tool Use and User Performance

A Study of Community Health Workers in the Kenyan Context

Maradona Gatara and Jason F. Cohen

Department of Information Systems, University of the Witwatersrand (WITS),
1 Jan Smuts Avenue, Braamfontein, 2000, Johannesburg, South Africa

Keywords: Mobile-Health, Community Health Worker, Information and Communication Technologies for Development, Information and Communication Technologies for Community Health Workers, Healthcare Service Delivery, Kenya, Task-Technology Fit, Use, User Performance.

Abstract: Equipping Community Health Workers (CHWs) in resource-constrained settings with mobile-health or 'mHealth' tools has the potential to improve healthcare service delivery. mHealth tool functionality must however match CHW task needs before these tools are likely to have any significant impacts on CHW performance. This paper contributes by drawing on Task-Technology Fit theory to test the extent to which a match between CHW tasks and mHealth technology characteristics influences the performance of 201 CHWs using an mHealth tool in the counties of Siaya, Nandi, and Kilifi in Kenya. Results showed that the interaction of paired task and technology characteristics did not always impact mHealth tool use and user performance in the manner expected. When mHealth tool functions matched the task interdependence and information dependency needs of the CHWs then CHW performance increased but CHW performance decreased for some CHWs when mHealth functionality for time criticality and mobility was high. Moreover, while information dependency had an independent positive effect on mHealth tool use, CHWs came to depend less on the mHealth tool to support time criticality, interdependence, and mobility needs when functional support was high. These findings have implications for the design and deployment of mHealth tools.

1 INTRODUCTION

Many developing countries are deploying Community Health Workers (CHWs) to deliver lifesaving and high impact interventions at the household level. One way in which CHWs can be supported in their delivery of healthcare services is by equipping them with supplementary mHealth tools (Earth Institute, 2010; Liu, Sullivan, Khan, Sachs and Singh, 2011). These technologies promise an improvement in CHW performance by supporting their needs to access health data at points of care, coordinate and share health data with co-workers, and to facilitate mobility as CHWs travel to various household locations (Teo and Men, 2008; Junglas, Abraham and Ives, 2009; Yuan, Archer, Connelly and Zheng, 2010). Unfortunately, full-scale mHealth deployment has been limited with many unsustainable pilot projects that fail to scale up meaningfully (LeMaire, 2011; Liu et al., 2011). More substantive evidence is thus needed on how these technologies can be designed to match with CHW service tasks and improve their performance. The purpose of this paper is to address this gap by examining whether a 'match' between CHW tasks and mHealth technology characteristics, influences CHW performance. Task-technology fit theory provides the theoretical underpinning for the study. CHWs using an mHealth tool and operating in the Siaya, Nandi and Kilifi counties in Kenya formed the empirical context for the study. The results reported in this paper are part of a larger project into the use and impacts of mHealth on CHWs operating in Kenya.

Gatara M. and Cohen J..
Matching Task and Technology Characteristics to Predict mHealth Tool Use and User Performance - A Study of Community Health Workers in the Kenyan Context.
DOI: 10.5220/0005223504540461
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2015), pages 454-461
ISBN: 978-989-758-068-0

2 BACKGROUND

2.1 Task and Technology Characteristics in the mHealth Context

CHWs perform various health monitoring, promotion and referral tasks. These tasks are characterised by varying degrees of rigidity in time structuring e.g. promptly responding to medical emergencies versus occasional follow-up care. These tasks may also be interdependent (Teo and Men, 2008), such that they require the coordination and sharing of health data with practitioners in clinics and hospitals. Moreover, CHWs need to perform their tasks at varying locations (Yuan et al., 2010), as CHWs must travel to different households as the points at which they deliver healthcare services. At these points of care, the CHWs tasks may require them to access dynamic health data e.g. on the location of medical and field supplies or equipment needed during household visits (Yuan et al., 2010). The ability of CHWs to perform their tasks well can therefore be hampered by a lack of understanding of temporal needs such as time criticality. Spatial needs such as mobility, and information sensitive needs such as interdependence and information dependency, are equally important for typical monitoring, promotion, and referral tasks (Yuan et al., 2010). Thus, *Time Criticality*, *Interdependence*, *Mobility*, and *Information Dependency* emerge as critical task characteristics relevant to CHW work.

Technologies comprise tool or system functions that are intended to support users in the performance of their tasks (Goodhue and Thompson, 1995). In light of the critical CHW task needs outlined above, mobile technologies should allow time-critical notifications (for example via SMS) to be made to remind CHWs when a task has to be performed urgently (Yuan et al., 2010). mHealth tools can better equip CHWs to coordinate and share information with co-workers (Yuan et al., 2010), and also offer location-sensitive functionality by providing information to CHWs as they perform their tasks and move between households (Junglas et al., 2009; Yuan et al., 2009). mHealth tools should thus support CHW needs for *Time Criticality*, *Interdependence*, *Mobility*, and *Information Dependency* (Earth Institute, 2010). These complementary task and technology characteristics considered relevant to the Kenyan context are summarized in Table 1.

2.2 The Match between Task and Technology Characteristics in the mHealth Context

Task-Technology Fit (TTF) follows the premise that a user will use a technology if it meets their needs by providing adequate functional support for the user's task (Goodhue and Thompson, 1995; Dishaw and Strong, 1998). Although TTF can be examined using varied analytical schemes (Venkatraman, 1989) such as fit as moderation or fit as mediation, this study views fit as a theoretically defined match between two related variables (Venkatraman, 1989; Dishaw and Strong, 1998; Premkumar et al., 2005). In this study's context, this is the paired match between task characteristics, i.e. *Time Criticality*, *Interdependence*, *Mobility*, and *Information Dependency*, which reflect CHW needs, and technology characteristics, i.e. *Time Criticality Support*, *Interdependence Support*, *Mobility Support*, and *Information Dependency Support*, which reflect mHealth tool functions. Fit as

Table 1: Task and Technology Characteristics.

	Task (User Needs)	Technology (Tool Functions)
Time Criticality	Degree to which user needs to perform tasks urgently (Gebauer and Tang, 2008)	Degree to which tool supports urgency by providing timely alerts (Wixom and Todd, 2005; Junglas et al., 2009)
Interdependence	Degree to which user needs to coordinate with co-workers (Teo and Men, 2008)	Degree to which tool supports coordination by pooling information (Teo and Men, 2008)
Mobility	Degree to which user needs to move between locations (Yuan et al., 2010)	Degree to which tool supports user movement by tracking locations (Yuan et al., 2010)
Information Dependency	Degree to which user needs to access point of care data (Yuan et al., 2010)	Degree to which tool supports access to location-sensitive point of care information (Yuan et al., 2010)

Matching is depicted as a 4 x 4 matrix (see Figure 1) where TTF occurs along the diagonals as an interaction between complementary task and technology characteristics (Dishaw and Strong, 1998).

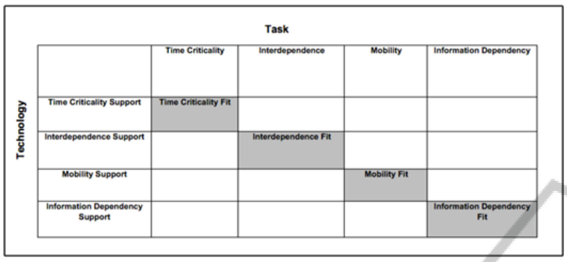

Figure 1: Task-Technology Fit (TTF) as Matching: 4 x 4 Matrix (Based on Dishaw and Strong, 1998).

As per TTF theory (Goodhue and Thompson, 1995), *Use and User Performance* are consequences of the fit resulting from a match between task and technology characteristics. *Use* can be defined in a number of ways, including as a dependency, described as the extent to which the user comes to rely on the technology (Junglas et al., 2009). *User Performance* is defined in terms of the effectiveness, efficiency, and quality with which the task is performed. Amongst CHWs, this implies task productivity, completion of tasks using minimal resources to do the most in the least amount of time, and whilst committing minimal errors with improved decision-making in the reporting of typical monitoring, promotion, and referral tasks. This study posits that the match between complementary pairs of task and technology characteristics will result in increased *Use and User Performance* (Teo and Men, 2008). In other words, the better the fit as a match between healthcare service task and mHealth tool characteristics, the more likely it is that CHWs will become dependent on the mHealth tool, and the more likely it is that their performance will be enhanced.

3 METHODS

3.1 Study Design

Data collection for this study formed part of a larger research project into the use and impacts of mHealth tools within the Kenyan CHW context. A structured survey instrument was administered to CHWs in Kenya, based in the county locations of Siaya, Nandi, and Kilifi. The instrument was used to elicit data from these CHWs on their task needs, their perceptions of the mHealth tools deployed to them, and their use of the mHealth tools in their work. Data was also collected on the performance of CHWs including both objective and perceptual measures of performance. Only the data collected on mHealth tool functionality, CHW task needs, CHWs dependence on the tool and its perceived performance impacts is reported in this paper.

3.2 Sampling Strategy

The research project relied on proportionate stratified sampling with systematic random sampling as the sampling strategy. In each county, Community Health Units (CHU's) made up of CHW's were targeted, and a proportional number was obtained from lists of CHWs operating in each of these units. The numbers drawn made up sampling frames for each of the three counties i.e. Siaya, Nandi, and Kilifi. Overall, 312 CHWs constituted the sampling frame devised, and subsequently participated in the project with 201 providing usable data for the purposes of this study.

3.3 Instrument Measurement

As reported elsewhere (Gatara and Cohen, 2014a; Gatara and Cohen, 2014b), to measure each construct, the instrument employed multi-item scales. To capture respondents' perceptions along the four task and technology characteristics, use, and user performance, 42 seven-point Likert scale items were used. These measures were drawn from prior validated instruments (Junglas et al., 2009; Gebauer and Tang, 2008; Lin and Huang, 2008; Teo and Men, 2008; Wixom and Todd, 2005; Yuan et al., 2010), and then refined through pre and pilot testing.

Time Criticality items reflected CHW needs to respond urgently, and start and finish tasks on time. *Interdependence* items reflected CHW needs to coordinate and share information with co-workers, clinics, and hospitals. *Mobility* items reflected needs of CHWs to perform tasks as they move from one location to another. *Information Dependency* items reflected CHW needs for access to information on the location of medical supplies and equipment at points of care such as households. *Time Criticality Support* items reflected the mHealth tools rapid response functions and provision of timely data to CHWs. *Interdependence Support* items reflected the mHealth tool's coordination functions, in pooling of data from co-workers, hospitals, and clinics. *Mobility Support* items reflected the mHealth tools location tracking functions for CHWs on the ground. *Information Dependency Support* items reflected the mHealth tool's functions to identify inventory i.e. medical supplies and equipment at points of care. The variables employed to measure *Use* comprise three perceptual seven-point Likert scale measures. The items reflect the degree to which CHWs became dependent on using the mHealth tool Junglas et al., 2009). *User Performance* measure comprised eight seven-point Likert scale measures reflecting CHW perception of *effectiveness*, *efficiency*, and *quality of care* (Junglas et al., 2009; Torkzadeh and Doll, 1999).

3.4 Computation of Task-Technology Fit as Matching

Task-Technology Fit was modelled using the interaction approach (Venkatraman, 1989), where Fit is modelled as a product of complementary pairs of task and technology characteristics as expressed in the following formula.

$$\boxed{\textit{Fit} = f\,(\textit{Task x Technology})}$$

Time Criticality Fit, Interdependence Fit, Mobility Fit, and Information Dependency Fit were each modelled in this way. These dimensions of Task-Technology Fit form the diagonals of the 4 x 4 matrix shown in Figure 1. The four *Fit* dimensions were tested for their effects on *Use* and *User Performance*. This was achieved using two models each for *Use* and *User Performance*, as expressed by the following equations.

$$(\textit{model } 0)\ \textit{Use/User Performance} = \alpha + \beta_1\,\textit{TaskCharacteristic} + \beta_2\,\textit{TechnologyCharacteristic} + \varepsilon,$$

$$(\textit{model } 1)\ \textit{Use/User Performance} = \alpha + \beta_1\,\textit{TaskCharacteristic} + \beta_2\,\textit{TechnologyCharacteristic} + \beta_3\,\textit{Fit} + \varepsilon,$$

The effects of each *Fit* dimension on *Use* and *User Performance* were tested by comparing a regression equation without *Fit* (model 0) to one with *Fit* (model 1), and using an F test to measure the significance of the change in R^2 values obtained (Dishaw and Strong, 1998). These models were tested separately for each fit dimension, and their effects on *Use* and *User Performance*. Results and analysis techniques are discussed in more detail in the next section.

4 RESULTS

4.1 Response Rate and Profile

A total of 201 usable responses were retained for analysis. Most CHWs as mHealth tool users were aged between 25 and 34 years (51%). In addition, the sample population comprised more female (63%) than male (37%) CHWs. The majority (74%), of respondents have been educated up to secondary school level. Moreover, a sizeable number (79%) of respondents have used mHealth tools for five months or more.

4.2 Findings and Discussion

Initial Principal Component Analysis (PCA) of the instrument measures was carried out, leading to the removal of four *User Performance* items, three *Time Criticality* items, two *Interdependence* items, and one *Mobility Support* item. The remaining item measures were then assessed for discriminant validity, internal consistency reliability, and unidimensionality (Hair, Hult, Ringle and Sarstedt, 2014) using Confirmatory Factor Analysis (CFA) techniques. Overall, the measurement model demonstrated adequate reliability and validity. Tests of the base and *Fit* models could then proceed.

4.3 Base Models: Use and User Performance

To test the base model (model 0) for *Use* as a dependent variable, Partial Least Squares – Structural Equation Modeling (PLS-SEM) was used to obtain estimates for the model i.e. the path coefficients representing the hypothesized relationships between each of the four sets of task and technology characteristics, and *Use*. To test the significance of the path coefficients, a bootstrapping procedure (using 500 samples; 201 cases) was run (Hair et al., 2014). Table 2 summarizes the R^2 obtained after estimating the reflective base models, with *Use* and *User Performance* as the dependent variables.

4.4 Fit as Matching: Effects on mHealth Tool Use

To test the Matching perspective, Fit, calculated as the paired interaction between corresponding task and technology characteristics, was included with tests of the structural models. The inclusion of the

Fit variable allows for the added effects of this match between the task and the technology, and its effects on Use to be estimated. For each interaction model, an f^2 effect size (Hair et al., 2014) was measured to assess whether the inclusion Fit had a substantive impact on Use. The Fit term for the *Time* Criticality, Interdependence, Mobility, and *Information* Dependency models, each explaining the dependent variable *Use* had small f^2 effect sizes of 0.0028, 0.015, 0.071, and 0.031 respectively, with *Information Dependency* Fit having the largest effect (0.071) on *Use*. A bootstrapping procedure (using 500 samples; 201 cases) was run to test the significance of the PLS estimates.

Table 2: PLS Results of the Base Model Predicting Use and User Performance.

Base Model (0) R^2	Use	User Performance
Time Criticality	0.177	0.160
Interdependence	0.080	0.149
Mobility	0.070	0.183
Information Dependency	0.170	0.113

Results were contrary to initial expectations. It was found that CHWs who perceive high levels of functional support provided for their *Time Criticality*, *Interdependence*, and *Mobility* needs depend less on the mHealth tool. This could be explained by the concept of 'over-fit', which occurs when technology provides excessive functional support, causing 'slack' (Gupta, 2003). The interaction term *TimeC x TimeCSup* has a significant negative effect ($p < .05$) on *Use* (-0.159), showing that high need users depend less on tool use than low need users with increased functional support. Similarly, the interaction term *Inter x InterSup* has a significant negative effect ($p < .10$) on *Use* (-0.120), showing that high need users depend less on the tool than low need users when functional support is high. The interaction term *Mobil x MobilSup* also has a significant negative effect ($p < .01$) on *Use* (-0.266), showing that high need users depend less on the tool than low need users when functional support is high. The interaction term *InfoDep x InfoDepSup* has a significant negative effect ($p < .05$) on *Use* (-0.153), where dependence on the mHealth tool is relatively flat as the need for information dependency increases, whereas at lower levels of functional support, dependence on the mHealth tool increases more steeply as this need increases. *Information Dependency* however, is the only need that has an independent effect on *Use*.

4.5 Fit as Matching: Effects on User Performance

Interestingly, CHWs who perceive high levels of functional support provided for their *Time Criticality* and *Mobility* needs are less likely to provide effective, efficient, and high quality care. This is also attributed to over-fit, which may occur when the mHealth tool provides excessive functional support (Gupta, 2003). However, CHWs who perceive high levels of functional support provided for their *Interdependence* and *Information Dependency* needs are more likely to provide effective, efficient, and high quality care. With perceived lower levels of functional support, CHWs will be less likely to perform well. In areas of certain task needs, where higher need users may be experiencing 'under-fit' (Gupta, 2003), it may be more difficult to match tool support to their needs, whereas users who do not even recognize they have a need, can nevertheless perform better with a high functioning tool. The *Fit* term for the *Time Criticality, Interdependence, Mobility,* and *Information Dependency* models, each explaining the dependent variable *User Performance*, had f^2 effect sizes of 0.092, 0.048, 0.116, and 0.069 respectively, with *Mobility Fit* having a medium effect size (0.116) signifying the largest effect on *User Performance*. As was the case for the *Fit* model predicting *Use*, a bootstrapping procedure (using 500 samples; 201 cases) was run to test the significance of the PLS estimates. The interaction term *TimeC x TimeCSup* has a significant negative effect ($p < .01$) on *User Performance* (-0.287), showing that CHWs do not necessarily need higher functional support, as this may in fact hinder their performance by disrupting their established workflows. By contrast, the interaction term *Inter x InterSup* has a significant positive effect ($p < .01$) on *User Performance* (0.203), showing high need users perform better than low need users when the tool provides high functional support. *The interaction term Mobil x MobilSup has a significant negative effect* ($p < .01$) *on User performance (*-0.295), showing that higher need users are still satisfied that they provide effective, efficient, and high quality care without functional support. Lower need users however feel they provide better care with higher levels of functional support. The interaction term *InfoDep x InfoDepSup* has a significant positive effect ($p < .01$) on *User Performance* (0.248), confirming that users with more tool support will likely experience better performance outcomes.

5 DISCUSSION AND CONCLUSION

This study was based on the premise that by matching CHW tasks and mHealth technology characteristics, the impacts of mHealth tool use on CHW performance in the Kenyan context could be observed. We drew on task-technology fit theory to define match as the degree to which CHW needs reflected by task characteristics i.e. *Time Criticality*, *Interdependence*, *Mobility*, and *Information Dependency*, are supported by mHealth tool functions reflected by technology characteristics i.e. *Time Criticality Support*, *Interdependence Support*, *Mobility Support*, and *Information Dependency Support*. Aspects of this study are comparable to other studies of mobile work support (Yuan et al., 2010). Results provide important insights into how CHW needs and mHealth tool functions influence *Use* and *User Performance*. First, the study provides substantive evidence that when mHealth tools are designed to match required tasks they can enhance CHW performance. Second, findings can be used to inform design of mHealth tools to provide more adequate functional support for the most critical user needs. Third, by providing empirical insights on the

Table 3: PLS Results of the Interaction Models Predicting Use.

	Path Coefficients	t Values	p Values	Significance Levels	90% Confidence Intervals
Time Criticality Model $R^2 = 0.199$, $f^2 = 0.028$					
TimeC → Use	0.099	1.65	0.10	*	[0.00, 0.20]
TimeCSup→ Use	0.371	4.67	0.00	***	[0.24, 0.50]
Fit (TimeC x TimeCSup) → Use	-0.159	2.09	0.05	**	[-0.29, -0.03]
Interdependence Model $R^2 = 0.094$, $f^2 = 0.015$					
Inter → Use	0.042	0.77	0.44	NS	[-0.05, 0.13]
InterSup→ Use	0.261	3.50	0.00	***	[0.25, 0.38]
Fit (Inter x InterSup) → Use	-0.120	1.81	0.07	*	[-0.23, -0.01]
Mobility Model $R^2 = 0.132$, $f^2 = 0.071$					
Mobil → Use	0.014	0.28	0.78	NS	[-0.07 0.10]
MobilSup→ Use	0.244	3.43	0.00	***	[0.13, 0.36]
Fit (Mobil x MobilSup) → Use	-0.266	3.69	0.00	***	[-0.38 -0.15]
Information Dependency Model $R^2 = 0.195$, $f^2 = 0.031$					
InfoDep → Use	0.192	2.54	0.01	**	[0.07, 0.32]
InfoDepSup→ Use	0.320	3.97	0.00	***	[0.19, 0.45]
Fit (InfoDep x InfoDepSup) → Use	-0.153	1.96	0.05	**	[-0.28, -0.02]

Note: NS = Not Significant. $^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$.

Table 4: PLS Results of the Interaction Models Predicting User Performance.

	Path Coefficients	t Values	p Values	Significance Levels	90% Confidence Intervals
Time Criticality Model $R^2 = 0.231$, $f^2 = 0.092$					
TimeC → User Perf	0.156	1.79	0.08	*	[0.01, 0.30]
TimeCSup→ Use Perf	0.268	3.57	0.00	***	[0.15, 0.39]
Fit (TimeC x TimeCSup) → User Perf	-0.287	2.96	0.00	***	[-0.45, -0.13]
Interdependence Model $R^2 = 0.188$, $f^2 = 0.048$					
Inter → User Perf	0.037	0.69	0.49	NS	[-0.05, 0.12]
InterSup→ User Perf	0.385	4.42	0.00	***	[0.23, 0.53]
Fit (Inter x InterSup) → User Perf	0.203	2.90	0.00	***	[0.09, 0.32]
Mobility Model $R^2 = 0.268$, $f^2 = 0.116$					
Mobil → User Perf	0.043	0.85	0.40	NS	[-0.04 0.13]
MobilSup→ User Perf	0.411	6.70	0.00	***	[0.31, 0.51]
Fit (Mobil x MobilSup) → User Perf	-0.295	3.86	0.00	***	[-0.42 -0.17]
Information Dependency Model $R^2 = 0.170$, $f^2 = 0.069$					
InfoDep → User Perf	0.178	2.17	0.03	**	[0.04, 0.31]
InfoDepSup→ User Perf	0.277	3.35	0.00	***	[0.14, 0.41]
Fit (InfoDep x InfoDepSup) → User Perf	0.248	2.90	0.00	***	[0.11, 0.39]

Note: NS = Not Significant. $^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$.

fit between healthcare service and mHealth tool characteristics from a matching perspective, the study findings can better inform mHealth tool use by CHWs and enhance performance in their capture, storage, transmission, and retrieval of health data (Liu et al., 2011). In the areas of *Information Dependency* and *Interdependence,* 'Fit as Matching' provides the best explanations for performance outcomes. However, findings also indicate that just because CHWs have needs does not mean that a highly functional tool necessarily results in increased dependency on *Use* or enhanced *User Performance*. Similarly, just because CHWs do not recognize a need, does not mean a high functioning tool cannot influence their dependence on *Use* or enhanced *User Performance*. The tool could be compensating for those who have not recognized a need and therefore have not already established routines and coping mechanisms. However, for those who have recognized a need, the tool may be unimportant given already established preferred practices. The study confirms that mobile technologies could improve mHealth tool use and CHW performance in low-resource community household settings (Earth Institute, 2010). However, designers should be cautious of excessive functional support that may hinder CHW performance with established routines, and that despite high mobility and time criticality needs, an mHealth tool may not always provide the best support. If function support is excessive, users may depend less on the tool, and its impacts may not be favourable at all levels of need. These results can nevertheless add to the growing interest in directly supporting CHWs at the point of care. Future research may wish to consider cost implications as instrumental to the successful deployment of mHealth platforms in the Kenyan context. Future work may also consider assessing the match between CHW needs and mHealth tool functions in other contexts and settings.

ACKNOWLEDGEMENTS

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

REFERENCES

Dishaw, M. T. and Strong, D. M. (1998) Supporting Software Maintenance With Software Engineering Tools: A Computed Task- Technology Fit Analysis. *The Journal of Systems and Software*, 44, 107-120.

Earth Institute, "One Million Community Health Workers: Technical Taskforce Report", 2010, http://www.milleniumvillages.org/uploads/ReportPaper/1mCHW_Technical TaskForceReport.pdf [last accessed 30th August 2014].

Torkzadeh, G. and Doll, W. 1999. The Development of a Tool for Measuring the Perceived Impact of Information Technology on Work. *The International Journal of Management Science,* 27, 1, 327-339.

Gatara, M., and Cohen, J. F., 2014a. Mobile-Health Tool Use and Community Health Worker Performance in the Kenyan Context: A Task-Technology Fit Perspective. In *Proceedings of the South African Institute for Computer Scientists and Information Technologists SAICSIT Conference* (Centurion, Gauteng, South Africa, September 28 – October 01 2014).

Gatara, M., and Cohen, J. F., 2014b. The Mediating Effect of Task-Technology Fit on mHealth Tool Use and Community Health Worker Performance in the Kenyan Context. In *Proceedings of the 8th International Development Informatics Association IDIA Conference* (Port Elizabeth, South Africa, November 03-04, 2014).

Gebauer, J. and Tang, Y. 2008. Applying the Theory of Task-Technology Fit to Mobile Technology: The Role of User Mobility. *Working Paper Abstract*, 1-23.

Goodhue, D. L. and Thompson, R. L. 1995. Task-Technology Fit and Individual Performance. *MIS Quarterly* 19, 2, 213-236.

Gupta, S. 2003. Knowledge Management and Performance: A Fit Perspective. *In Proceedings of the Ninth Americas Conference on Information Systems* (Tampa, Florida, USA, August 04-06, 2003).

Hair, J. F, Hult, G. T, Ringle, C. M. and Sarstedt, M. 2014. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage, Thousand Oaks, California.

Junglas, I., Abraham, C., and Ives, B. 2009. Mobile Technology at the Frontlines of Patient Care: Understanding Fit and Human Drives in Utilization Decisions and Performance, *Decision Support Systems*. 46, 534- 647.

LeMaire, J. "Scaling Up Mobile Health: Elements for the Successful Scale Up of mHealth in Developing Countries", 2011 http://www.k4health.org/sites/sites/default/files/ADA_mHealth%20White%20Paper.pdf [last accessed 2nd May 2013].

Lin, T. and Huang, C. 2008. Understanding Knowledge Management System Usage Antecedents: An Integration of Social Cognitive Theory and Task-Technology Fit. *Information and Management*, 45, 410-417.

Liu, A, Sullivan, S, Khan, M. Sachs, G. and Singh, P. 2011. Community Health Workers in Global Health: Scale and Scalability, *Mount Sinai Journal of Medicine*, 78, 1, 419-435.

Teo, S. H. and Men, B. 1999. Knowledge Portals in Chinese Consulting Firms: A Task-Technology Fit Perspective. *European Journal of Information Systems*, 17,1, 2008, pp. 557-574.

Venkatraman, N. 1989. The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence. *The Academy of Management Review*, 14, 3, 423-444.

Wixom, B. H. and Todd, P. A. 2005. A Theoretical Integration of User Satisfaction and Technology Acceptance, 16, 1, 85-102.

Yuan, Y., Archer, N., Connelly, C. E. and Zheng, W. 2010. Identifying the Ideal Fit Between Mobile Work and Mobile Work Support. *Information and Management*, 47, 125-137.