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Mobile Technology-Enabled Healthcare Service Delivery Systems for Community Health Workers in Kenya: A Technology-to-Performance Chain Perspective

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy (Ph.D.) in Information Systems (IS)

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Declaration

I hereby declare that this thesis is my own unaided work, except as acknowledged in the text.

It is being submitted for the Degree of Doctor of Philosophy (Ph.D.) in Information Systems (IS) to the University of the Witwatersrand (WITS), Johannesburg, South Africa.

It has not been submitted, in whole or in part, for any other degree or examination, at this or any other institution.

Signed …………………………

M.C. Gatara

November 2016

Dedication

To God the creator, for blessing me with the grace and strength through which all is possible.

To Mum and Dad, for their love, inspiration, support, and encouragement from the beginning.

To Ms. Juliana Kibatta, a very special friend, for her love, companionship and support.

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Preface

Parts of this thesis have already been published in scientific peer-reviewed publications, including:

The *Journal for Health Informatics in Africa (JHIA)* in conjunction with proceedings of the *8th Health Informatics in Africa Conference (HELINA)* 2013 and *9th Health Informatics in Africa Conference (HELINA)* 2015; the *8th International Development Informatics Association Conference (IDIA)* 2014; the *8th International Conference on Health Informatics (HEALTHINF)* 2015; the *Southern African Institute for Computer Scientists and Information Technologists (SAICSIT)* 2014; and as contributions to the book text *mHealth Ecosystems and Social Networks in Healthcare* (Springer International Publishing) 2016.

This universal acceptance and endorsement by the scholarly and scientific research community has lent credence and provided impetus to the production of this thesis.

In all cases, the published works have been re-formatted, updated, and synthesized into this thesis.

Abstract

Community Health Workers or "CHWs" are often the only link to healthcare for millions of people in the developing world. They are the first point of contact with the formal care system, and represent the most immediate and cost effective way to save lives and improve healthcare outcomes in low-resource contexts. Mobile-health or 'mHealth' technologies may have potential to support CHWs at the point-of-care and enhance their performance.

Yet, there is a gap in substantive empirical evidence on whether the use of mHealth tools enhances CHW performance, and how their use contributes to enhanced healthcare service delivery, especially in low-resource communities. This is a problem because a lack of such evidence would pose an obstacle to the effective large-scale implementation of mHealth-enabled CHW projects in low-resource settings.

This thesis was motivated to address this problem in the Kenyan community health worker context. First, it compared the performance of CHWs using mHealth tools to those using traditional paper-based systems. Second, it developed and tested a replicable Technology-to-Performance Chain (TPC) model linking a set of CHW task and mHealth tool characteristics, to use and user performance outcomes, through four perspectives of Task-Technology Fit (TTF), namely Matching, Moderation, Mediation, and Covariation.

A quasi-experimental post-test only research design was adopted to compare performance of CHWs using an mHealth tool to those using traditional paper-based systems. A primary structured questionnaire survey instrument was used to collect data from CHWs operating in the counties of Siaya, Nandi, and Kilifi, who were using an mHealth tool to perform their tasks (n = 257), and from CHWs operating in the counties of Nairobi and Nakuru using traditional paper-based systems to perform their tasks (n = 353). Results showed that CHWs using mHealth tools outperform their counterparts using paper-based systems, as they were observed to spend much less time completing their monitoring, prevention, and referral reports weekly, and

report higher percentages of both timeous and complete monthly cases. In addition, mHealth tool users were found to have more positive perceptions of the effects of the technology on their performance, compared to those using traditional paper-based systems.

An explanatory, predictive, research design was adopted to empirically assess the effects of a 'fit' between the CHW task and mHealth technology (TTF) on use of the mHealth technology and on CHW user performance. TTF was tested from the Matching, Moderation, Mediation, and Covariation 'fit' perspectives using the cross-sectional survey data collected from the mHealth tool users (n = 257). Results revealed that there are various unique ways in which a 'fit' between the task and technology can have significant impacts on use and user performance. Specifically, results showed that the paired-match of time criticality task and technology characteristics impacts use, while that of time criticality and information dependency task and technology characteristics impacts user performance. Results also showed that the cross-product interaction of mobility task and interdependence technology characteristics impacts use, and that of mobility task and interdependence and information dependency technology characteristics, impacts user performance. Similarly, the cross-product interaction of information dependency task and time criticality technology characteristics impacts user performance. Moreover, results showed that a perceived 'fit' between CHW task and mHealth technology characteristics partially and fully mediates the effects of user needs and tool functions on use and user performance, whereas 'fit' as an observed pattern of holistic configuration among these task and technology characteristics impacts use and user performance. It was also found that the perfect 'fit' between CHW task and mHealth tool technology characteristics leads to the highest levels of use and user performance, while a misfit leads to a decline in use and user performance. Notably, an over-fit of mHealth technology support to the CHW task leads to declining use levels, while an under-fit leads to diminishing user performance. Of the four 'fit' perspectives tested, the matching and cross-product interaction of task and technology characteristics offer the most dynamic insights into use and user performance impacts, whereas user-perception and holistic configuration, were also shown to be significant, thus further reinforcing these effects. Tests of a full TPC model revealed that greater mHealth tool use had a positive effect on the effectiveness, efficiency, and quality of CHW

performance in the delivery of patient care. Moreover, it was found that ‘facilitating conditions’ and ‘affect toward use’ had positive effects on mHealth tool use. Furthermore, a perceptual TTF was found to have positive effects on mHealth tool use and CHW performance. Of note, this perceived TTF construct was found to be simultaneously a stronger predictor of mHealth tool use than ‘facilitating conditions’ and ‘affect toward use’, and a stronger predictor of CHW performance than mHealth tool use. Consequently, TTF was confirmed as the central construct of the TPC.

The findings constitute significant empirical insights into the use of mHealth tools amongst CHWs in low resource settings and the extent to which mHealth contributes to the enhancement of their overall performance in the capture, storage, transmission, and retrieval, of health data as part of their typical workflows. This study has provided much needed evidence of the importance of a ‘fit’ between CHW task and mHealth technology characteristics for enabling mHealth impacts on CHW performance. The study also shows how these inter-linkages could improve the use of mHealth tools and the performance of CHWs in their delivery of healthcare services in low-resource settings, within the Kenyan context. Findings can inform the design of mHealth tools to render more adequate support functions for the most critical CHW user task needs in a developing world context.

This study has contributed to the empowerment of CHWs at the point-of-care using mHealth technology-enabled service delivery in low-resource settings, and contributes to the proper and successful ‘scaling-up’ of implemented mHealth projects in the developing world.

Keywords: Mobile-Health (mHealth), Community Health Workers (CHWs), Technology-to-Performance Chain (TPC), Task-Technology Fit (TTF), Use, Precursors of Use, User Performance, Quasi-Experimental Post-Test-Only Design, Partial Least Squares – Structural Equation Modeling (PLS – SEM), Polynomial Regression, Response Surface Methodology, Mobile Informatics, Health Informatics, Kenya, Africa, Developing Countries

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1 Introduction to the Problem of Mobile-Health (mHealth) and Community Health Worker (CHW) Performance

1.1 The Promise of Mobile Health (mHealth)

"Mobile Health", otherwise known as "mHealth", is defined as the use of mobile devices to enhance service delivery within healthcare systems (Mechael, 2009; van Heerden, Tomlinson and Swartz, 2012). The use of mHealth tools promises greater access to service for populations particularly within developing country and low resource settings[1]. Moreover, mHealth can create cost efficiencies and improve the capacity of health systems to facilitate the provision of quality patient care (Lasica, 2007). The uptake of mHealth technologies can enhance point-of-care data collection, patient communication, and real-time medication adherence support (Tomlinson, Solomon, Singh and Doherty, 2009). The mobile platform can support the delivery of healthcare services to wherever people are. Thus the utilization of mHealth can be effective in addressing the challenges of reaching underserved populations in remote areas, and improving patient care. Despite the promise and potential of mHealth, developing country contexts have been characterized by unsustainable pilot projects that often expire once initial funding is exhausted (LeMaire, 2011). Because few studies have been conducted in low-resource settings to date, there are gaps in substantive evidence of impacts on healthcare (Earth Institute, 2010; Tomlinson, Rotheram-Borus, Swartz and Tsai, 2013). Furthermore, there is a persistent lack of understanding of how to evaluate the contribution of mHealth devices to enhanced patient care (Pop-Eleches, Thirumurthy, Habyarimanaa, Zivin, Goldstein, De Walque, MacKeen, Haberer, Kimaiyo and Sidle, 2011; Siedner, Haberer, Bwana, Ware and Bangsberg, 2012). This is characterized by a lack of evidence that poses an obstacle to effective large-scale implementation of mHealth projects (Collins, 2012). Consequently, there is a growing demand for scientific research in low-resource, developing country settings to evaluate if and how equipping health workers with mHealth tools impacts their performance in health service delivery. Accordingly, the application of rigorous methodology to generate quality evidence has since emerged as a key priority (Philbrick, 2013).

[1] A low-resource setting is an area characterized by poor infrastructure and limited access to basic needs and services, and covers low-income countries, but also includes areas in middle or high income countries where under-served populations encounter difficulties accessing specialized healthcare (Wootton and Bonnardot, 2015).

1.2 The Community Health Worker (CHW)

Community Health Workers or “CHWs”, are often the only link to patient care for millions of people in the developing world. In the absence of medical professionals, CHWs are the first point of contact with the formal care system (Global Health Workforce Alliance, 2010). They cost comparatively little to train but can deliver life-saving, high-impact interventions in areas such as hygiene, sanitation, reproductive health, first aid, vaccinations, and oral rehydration therapy for infants. In some developing countries, CHWs have been deployed to identify, refer and even administer basic treatment for illnesses at the household level (Liu, Sullivan, Khan, Sachs and Singh, 2011). Due to their important role in health service delivery, there has been an increasing need to support CHWs at the point-of-care (Liu et al., 2011; Perry and Zulliger, 2012). The use of mHealth tools by CHWs at the point-of-care could enable their access to information, provide them with adequate decision-support, and enhance their timeliness in emergency responses and effectiveness in monitoring and disease surveillance (Mechael, 2009; Earth Institute, 2010, p. 36; Perry and Zulliger, 2012). Therefore incorporating mHealth tools into their workflows could enhance the capacity of CHWs to effectively link patients to the formal care system (Braun, Catalani, Wimbush and Israelski, 2013, p. 5) and improve patient care in low-resource settings (Earth Institute, 2010; LeMaire, 2011). Unfortunately, there remains limited evidence of the impacts of mHealth on the service delivery performance of CHWs in low-resource settings (Perry and Zulliger, 2012; Braun et al., 2013). This is a problem because a lack of such evidence would pose an obstacle to the effective large-scale implementation of mHealth-enabled CHW projects in low-resource settings. Consequently, there is a need for rigorous empirical evaluation of the link between mHealth tool use and CHW performance (Braun et al., 2013, p. 5). Moreover, frameworks with which to evaluate the mHealth-enabled support of CHWs at the point-of-care are needed (Tariq and Akter, 2011). These frameworks could be useful for the design of effective mHealth tools to enhance the performance of CHWs in meeting local needs through the provision of patient care at the household level (Illuyemi, Fitch, Parry and Briggs, 2010).

1.3 Problem and Research Questions

There are several research questions that arise from the knowledge gaps discussed in sections 1.1 and 1.2. These questions concern the impacts of mHealth tool use on CHW performance, how this use is influenced by a fit of the technology used to the task performed, and other factors.

First, CHWs in low-resource settings have traditionally used paper-based systems as reporting tools (Singh and Sullivan, 2011). Replacing these conventional tools with mHealth platforms has increasingly become a subject of interest. However, accompanying evidence of mHealth tool use impacts on the performance of CHWs in their delivery of patient care is needed (Braun et al., 2013). Moreover, rigorous evaluation with comparable CHW performance indicators in specific developing country contexts is called for (Tomlinson et al., 2013). To address these knowledge gaps, Research Questions 1 and 2 are formulated:

1. What are the differences in CHW performance using mHealth tools compared to those using traditional paper-based systems?
2. How are these differences indicative of expected positive mHealth tool impacts on CHW performance?

Second, there is a need for rigorous research to inform the design of mobile technologies for enhanced CHW performance. In this regard, it is important to understand what functional requirements are important for specific CHW tasks (Global Health Workforce Alliance, 2010). Furthermore, there appears to be a lack of frameworks with which to systematically evaluate whether mHealth tools fit CHW needs, and to assess CHW performance as a consequence of this fit (Tariq and Akter, 2013). To address these knowledge gaps, Research Questions 3 and 4 are formulated:

3. How can a fit between mHealth tools and CHW tasks be conceptualized?
4. To what extent does this fit impact mHealth tool use and CHW performance?

Third, there appears to be little, if any, substantive evidence of what factors may contribute to, or facilitate, mHealth tool use in low-resource settings. In addition, there is a need for more rigorous research on the extent to which the use of an mHealth tool impacts CHW performance. To address these knowledge gaps, Research Questions 5 to 7 are formulated:

5. What are the determinants of mHealth tool use by CHWs?
6. To what extent do these determinants impact mHealth tool use by CHWs?
7. To what extent does mHealth tool use impact CHW performance?

The Study Objectives identified to address these seven Research Questions, are discussed in Section 1.4.

1.4 Study Objectives

To answer the research questions formulated in Section 1.3, a set of objectives are specified. First, to answer Research Questions 1 and 2, the following objectives are specified:

1. Identify a relevant set of dimensions with which to evaluate CHW performance.
2. Use these dimensions to compare the performance of CHWs using an mHealth tool to those using a paper-based system.

Second, to answer Research Questions 3 and 4, the following study objectives are specified:

3. Identify a relevant set of dimensions with which to evaluate CHW tasks and mHealth tools.
4. Use these dimensions to operationalize the fit between CHW tasks and mHealth tools.
5. Examine the impact of this fit on mHealth tool use and CHW performance.

Third, to answer Research Questions 5, 6, and 7, the following study objectives are specified:

6. Identify a relevant set of dimensions to evaluate mHealth tool use precursors.
7. Using these dimensions, examine the impact of precursors on mHealth tool use.
8. Identify a relevant set of dimensions with which to evaluate mHealth tool use.
9. Use these dimensions to examine the impact of mHealth tool use on performance.

To achieve Study Objectives 1 and 2, CHWs using an mHealth tool were compared to those using a paper-based system. To achieve Study Objectives 3 to 9, a conceptual model linking technology to use and user performance, through its fit with the task, was developed to guide the present study. This conceptual model, a Technology-to-Performance Chain (TPC), is described in Section 1.5.

1.5 The Technology-to-Performance Chain (TPC)

The Technology-to-Performance Chain (TPC) (Goodhue, 1992; Goodhue and Thompson, 1995), depicted in Figure 1.1, was developed to address Study Objectives 3 to 9. The TPC is a causal model underpinned by the theory of Task-Technology Fit (TTF), which can be traced to the perspectives of Cognitive Fit (Vessey, 1991; Vessey and Galleta, 1991; Vessey, 1994), and Task-System Fit (Goodhue, 1992; Goodhue, 1994; Goodhue, 1995). In the present study, the TPC is a conceptual model linking task and technology characteristics to mHealth tool use and CHW performance through four perspectives of 'fit' (Venkatraman, 1989).

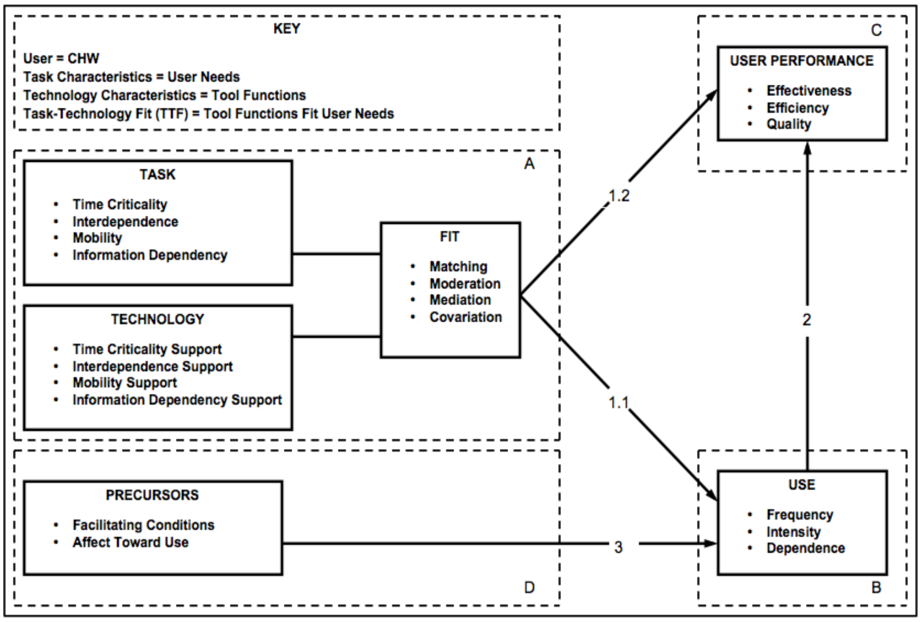

Figure 1.1. Conceptual Model

This conceptual model comprises the four constructs of TTF (A), use (B), user performance (C), and precursors of use (D). These constructs are the components of a TPC. TTF, the core component of this TPC, is linked first to use (Link 1.1) and second to user performance (Link 1.2). The TTF outcomes of use and user performance are concurrent[2]. As per the traditional TTF (Fit-Focus) model (Goodhue and Thompson, 1995), technological support of the task is expected to influence both use and user performance (p. 215). TTF is conceptualized using four perspectives of 'fit' (Venkatraman, 1989) operationalized as Matching, Moderation, Mediation, and Covariation. Third, use is linked to user performance (Link 2). The traditional TTF (Fit-Focus) model is therefore extended to form a complete TPC, such that user performance is considered a function of both TTF and use (Goodhue, 1992; Goodhue and Thompson, 1995, p. 216). Fourth, precursors are linked to use (Link 3). The completed TPC is thus extended such that use is considered a function of both TTF and a set of precursors (Goodhue, 1992, p. 305). The TPC was used to examine mHealth impacts on CHW performance in low-resource developing country settings. The context for the present study is discussed in Section 1.6.

[2] It is recognized in this study that in performing the task, the user is using the technology. The TTF outcomes of use and user performance are discussed in detail in Section 4.6.5 of Chapter 4.

1.6 Context of the Study

The use of mHealth tools by CHWs deployed in low-resource developing country settings informs the context of the study. To link households to the formal care system, these CHWs deliver patient care by performing reporting, monitoring, prevention, and referral tasks. The study context is informed by the implementation of mHealth projects in Kenya, an emerging developing country. As participants in these projects, CHWs are equipped with mHealth tools used to deliver patient care during household visits. Kenya represents a microcosm of global mHealth CHW initiatives. Kenya has among the highest mobile penetration rates [3] in the developing world (Ngugi, Pelowski and Ogembo, 2010). Moreover, Kenya is a leading country in mobile technology-enabled innovation (Aker and Mbiti, 2010). Furthermore, Kenya is at the forefront of global mHealth community projects in low-resource settings (LeMaire, 2011), and is attractive to international development partners investing in mobile technology-enabled service delivery platforms (Zambrano and Seward, 2012). Chapter 2 expands the discussion of the research context and the study setting.

1.7 Methodology of the Study

The methodology used in the present study, is depicted as a layered schematic in Figure 1.2.

[3] According to the most recent statistical report from the Communications Authority of Kenya (CAK), there are 37.8 million subscribers in Kenya, and the mobile penetration rate currently stands at 88% (Communications Authority of Kenya, 2016).

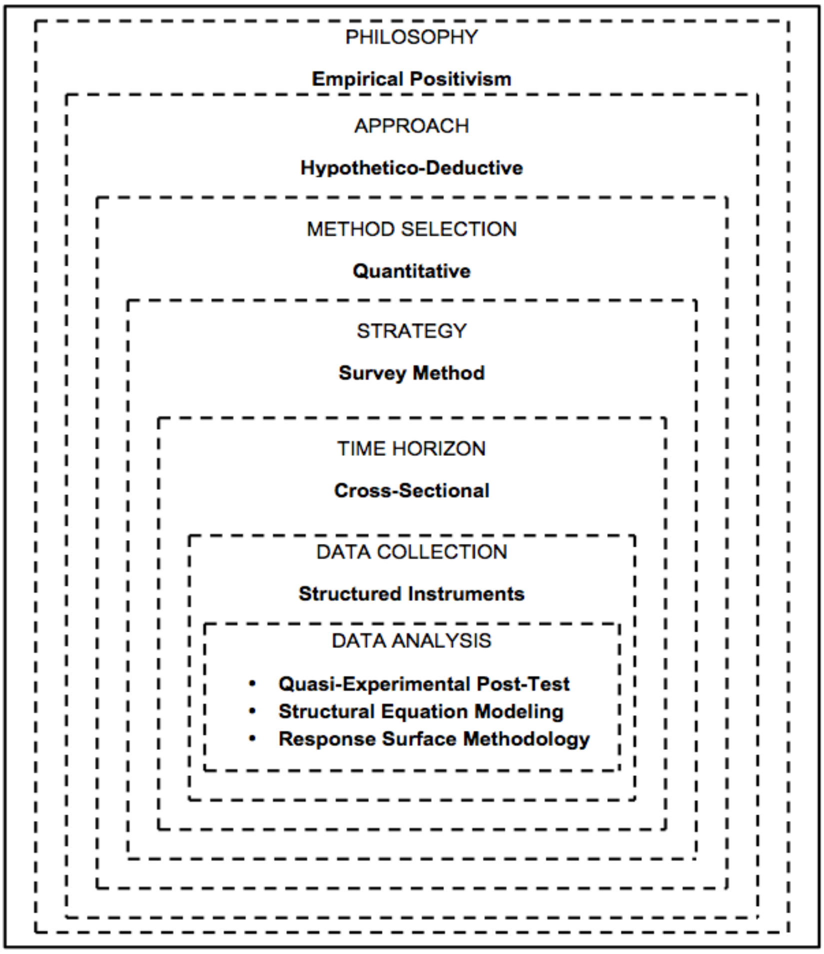

Figure 1.2. Methodology of the Study

The present study was informed by a philosophy consistent with empirical positivism (Straub, Boudreau and Gefen, 2004), the objective expression of reality using causal relationships to test theories and concepts (Orlikowski and Baroudi, 1991; Bhattacherjee, 2012, p. 18). The method selection for the study was quantitative (Creswell, 2009). A cross-sectional survey strategy (Saunders, Lewis and Thornhill, 2012, p. 190) was used in the study. Structured questionnaire instruments (Orlikowski and Baroudi, 1991) were developed and used to collect data from respondent CHWs in Kenya. These CHWs were operating within peri-urban communities in the counties of Siaya, Nandi, Kilifi, Nairobi, and Nakuru.

First, to address Study Objectives 1 and 2 and answer Research Questions 1 and 2, a quasi-experimental research design was adopted (Harris, McGregor, Perencevich, Furino, Zhu, Peterson and Finkelstein, 2006). A quasi-experimental post-test was conducted to compare the performance of CHWs using an mHealth tool versus those using a paper-based system. Data from cross-sectional surveys were analysed using first generation[4] multi-variate techniques[5] (Hair, Black, Babin and Anderson, 2010) including Analysis of Covariance (ANCOVA) and Sequential (Hierarchical) Regression (Brace, Kemp and Snelgar, 2012).

Second, to Study Objectives 3 to 9 and answer Research Questions 3 to 7, an explanatory, predictive research design was adopted to understand relationships between theoretical constructs and their underlying causes (Gregor, 2006). To empirically test these relationships, a hypothetico-deductive approach is used (Kaplan and Duchon, 1988). This approach was used in the present study to empirically test (1) the ‘fit’ between the mHealth tool and CHW task, and its effects on use and user performance, (2) the effects of mHealth tool use on CHW performance, and (3) the effects of precursors on mHealth tool use. Data from cross-sectional surveys were analysed using Partial Least Squares – Structural Equation Modeling (PLS-SEM)[6], a component-based, second-generation[7], statistical path modeling technique (Hair, Hult, Ringle and Sarstedt, 2014). Path modeling is described as the use of diagrams to visualize systematically related propositions examined via Structural Equation Modeling (SEM) and underpinned by theory (Hair, Ringle and Sarstedt, 2011). Response Surface Methodology (RSM) with Polynomial Regression (Edwards, 2002)[8] was used to extend empirical testing of the ‘fit’ between the mHealth tool and CHW task (TTF), to account for non-linear interaction effects on use and user performance (Shanock, Baran, Gentry, Pattison and Heggestad, 2010).

The research designs employed to address Study Objectives 1 to 9 and answer Research Questions 1 to 7 are summarized in Table 1.2.

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[4] First-generation techniques have been classified as the primarily exploratory methods of cluster analysis, exploratory factor analysis, and multi-dimensional scaling, and the primarily confirmatory methods of Analysis of Variance (ANOVA), logistic regression, and multiple regression (Hair et al., 2014, p.2).
[5] Data analysis was conducted using the IBM SPSS (Version 22) software package for Windows.
[6] Data analysis was conducted using the SmartPLS (Versions 2 and 3) software package for Windows and Mac.
[7] Second-generation techniques encompass the Partial Least Squares (PLS) and Covariance Based (CB) approaches to Structural Equation Modeling (SEM), and include confirmatory factor analysis (Hair et al, 2014, p. 2).
[8] Data analysis was conducted using the SYSTAT (Version 13) software package for Windows.

Table 1.1. Research Design

Design	Research Questions	Study Objective	Description
Quasi-Experimental	1,2	1, 2	• A comparison of CHW performance using an mHealth tool versus paper-based system.
Explanatory, Predictive	3,4	3, 4, 5	Examine: • The effects of TTF as Matching on mHealth tool use and CHW performance. • The effects of TTF as Moderation on mHealth tool use and CHW performance. • The effects of TTF as Mediation on mHealth tool use and CHW performance. • The effects of TTF as Covariation on mHealth tool use and CHW performance.
	5, 6, and 7	6, 7, 8, 9	Examine: • The effect of precursors on mHealth tool use. • The effect of mHealth tool use on CHW performance.

The contributions of the present study to research and practice are highlighted in Section 1.8.

1.8 Contributions of the Study

In the present study, contributions were made to theory, methodology, practice, and context. The following is an overview of these theoretical, methodological, practical, and contextual contributions.

First, the study constitutes a contribution to theory through the conceptualization of a replicable Technology-to-Performance Chain (TPC) linking mHealth tools to CHW performance through Task-Technology Fit (TTF), which is a multi-faceted, multi-perspective construct, which forms the core of this conceptual model. The TPC is underpinned by the theory of TTF (Vessey, 1991; Vessey and Galleta, 1991; Goodhue, 1992; Goodhue, 1994; Vessey, 1994; Goodhue and Thompson, 1995). In developing this TPC, a set of mHealth tool and CHW task characteristics were adopted for use in the context of the study. The importance of TTF as a perspective from which to predict and explain the outcomes of tool use and user performance is demonstrated through its application to mHealth for community-oriented patient care in low-resource settings in Kenya. In addition to TTF positioned at its core, the TPC was completed through a ‘forward linkage’ between use and user performance, and a ‘backward linkage’ between a set of precursors and use.

Second, the study constitutes a contribution to methodology through the development of survey instrument scales for the measurement of (1) CHW task and mHealth tool characteristics, (2) the ‘fit’ between them, (3) mHealth tool use, (4) precursors of mHealth tool use, and (5) CHW performance. Moreover, the ‘fit’ between the task and technology (TTF) was operationalized from the four adopted ‘fit’ perspectives of Matching, Mediation, Moderation, and Covariation (Venkatraman, 1989). A quasi-experimental post-test-only design (Harris et al., 2006) was adopted to empirically examine the performance of CHWs using an mHealth tool compared to a traditional paper-based system. In addition, an explanatory, predictive design (Gregor, 2006) was adopted and used to empirically test the link between the mHealth tool and CHW performance through TTF and use constructs. This methodological contribution of the present study is conducive to the increasing need for rigorous, evidence-based study designs in mHealth research (Global Health Workforce Alliance, 2010).

Third, the study constitutes a contribution to practice through the establishment of a set of criteria with which to substantively evaluate the performance of CHWs as mHealth tool users in low-resource developing country settings. Specifically, eleven performance indicators were developed to examine the effectiveness, efficiency, and quality of CHWs in reporting tasks. Specifically, these indicators were used to evaluate task reporting performance criteria including CHW workload, flow time, error rate, and completeness metrics. Community project implementers in low-resource settings can use these CHW reporting performance criteria to better quantify impacts of mHealth tools compared to the more traditional paper-based systems. These quantifiable metrics serve as indicators of the expected positive impacts of mHealth tools on CHW performance, thereby informing implementers seeking to replace traditional paper-based reporting systems or enhance current mHealth tool support functions for task reporting. In addition, practicable criteria were established for the evaluation of (1) the fit between the CHW task and the mHealth tool, and its effects on use and user performance, (2) the effects of mHealth tool use on CHW performance, and (3) the effects of precursors of use on mHealth tool use. A

TPC was used to evaluate the inter-linkages between these constructs. This TPC can serve as a diagnostic tool with which mHealth practitioners could empirically assess how and why a ‘fit’ between mHealth tools and CHW tasks, impacts mHealth tool use and CHW performance in a particular context. The TPC can also be used to effectively explain the possible ways in which mHealth tool use is influenced, and itself influences CHW performance. The core mechanism or process of the TPC is a multi-faceted task-technology fit (TTF) construct, which can be transformed into a perspective-oriented evaluative framework with which to explain technology use and user performance, to inform the design of functionally supportive mHealth tools. Furthermore, of particular importance, the TPC and multi-perspective TTF mechanisms that were examined in the present study can be developed into analytic, evaluative, or classificatory frameworks informing any context, setting, or industry in which technology users are compelled to use tools or systems to perform their tasks. This practical contribution informs the need to (1) contribute to the design of effective mHealth technologies that enhance CHW performance in low-resource settings, (2) contribute to the design of effective technologies that enhance performance in multiple user environments, and (3) positively influence use and user performance behaviours.

Fourth, the study constitutes a contribution to context through the application of theory and quantitative methodology, to evaluate mHealth projects implemented in real-world settings, therefore representing practical solutions to currently existing global problems. In these projects, CHWs are equipped with mHealth tools and deployed in low-resource developing country settings, to deliver patient care at the household level. The use of mHealth tools and CHW performance in the Kenyan context was examined in conjunction with community projects aligned to inter-alia (1) the mHealth Alliance, (2) the Millennium Development Goals (MDGs), (3) the Global Health Workforce Alliance, and (4) Frontline Health Workers Coalition, as part of collaborative efforts with among others (1) the Government of Kenya (GOK) Ministry of Health (MOH) Division of Community Health Services (DCHS), (2), the United States Agency for International Development (USAID) sponsored APHIAplus project, and (3) The Africa Medical and Research Foundation (AMREF). This contextual contribution of the present study informs the need for evidence-based health service delivery policy in developing countries, through the mobile technology-enabled support of CHWs in low-resource settings, effectively linking households to the formal care system using mHealth tools at the point-of-care.

The structure of the present study and its contents are presented and summarized in Section 1.9.

1.9 Structure of the Study

The present study is structured as a thesis consisting of eleven chapters as shown in Figure 1.3. Given the design, research questions, and objectives of the study, the thesis is not structured as a typical monograph, and instead comprises an introductory chapter, a contextual background chapter, theoretical underpinnings and conceptual model development chapters, six empirical chapters within which methods and data analyses are embedded, and a conclusion chapter.

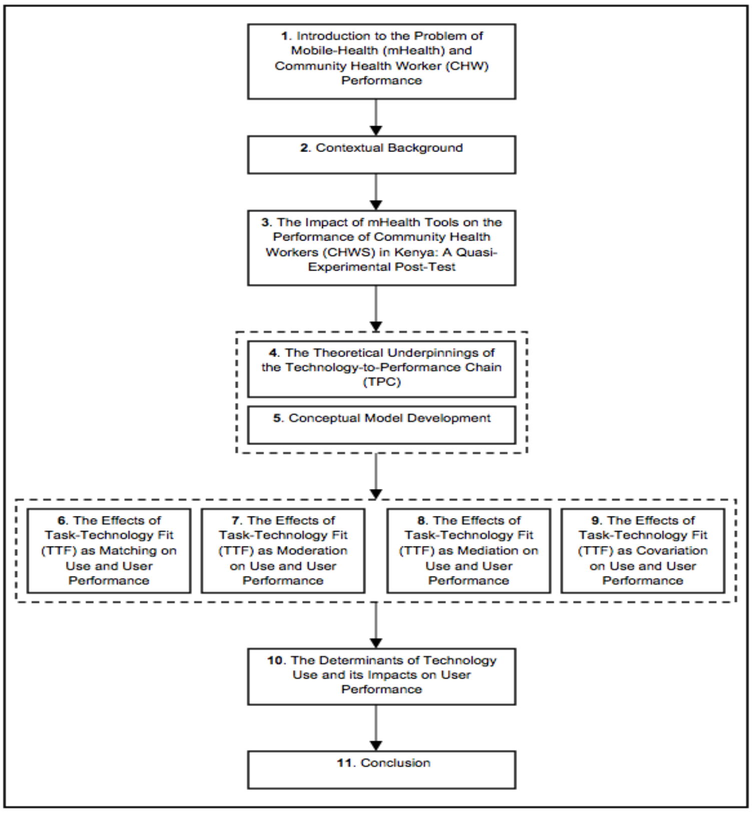

Figure 1.3. Structure of Thesis

In Chapter 2, the contextual background of this study is discussed. First, the existing literature on mHealth and CHW work in developing countries is reviewed. Second, typical examples of mobile technology applications for healthcare are identified. Third, shortcomings in prior works in the areas of mHealth and community health work are identified. Fourth, several implications of these shortcomings are derived.

In Chapter 3, the quasi-experimental post-test (Harris, McGregor, Perencevich, Furino, Zhu, Peterson and Finkelstein, 2006) that was conducted to compare the performance of CHWs using an mHealth tool with those using a traditional paper-based system, is reported on. For analysis, the multi-variate techniques of ANCOVA and Sequential (Hierarchical) Regression (Brace et al., 2012) were used.

In Chapter 4, the theoretical underpinnings of the study are discussed. First, existing literature pertaining to the theory of TTF (Vessey, 1991; Vessey and Galleta, 1991; Goodhue, 1992; Goodhue, 1994; Vessey, 1994; Goodhue and Thompson, 1995) is reviewed to inform the development of the study's technology-to-performance chain model. In Chapter 5, the TPC conceptual model is described in detail and the links between the concepts of TTF, use, user performance, and precursors of use, are developed.

In Chapter 6, the adoption and use of the Fit as Matching perspective (Venkatraman, 1989, p. 430) to examine the 'fit' between the CHW task and mHealth tool characteristics (TTF) and its effects on use and user performance, is described. This 'fit' was operationalized as the product of corresponding (complementary) pairwise task and technology characteristics. To assess the impact of TTF, continuous moderator effects were modelled using the PLS-SEM product indicator approach to create interaction terms (Hair et al., 2014). In Chapter 7, the adoption and use of the Fit as Moderation perspective (Venkatraman, 1989, p. 424) to examine the 'fit' between the CHW task and mHealth tool characteristics (TTF) and its effects on use and user performance, is described. This 'fit' was operationalized as the cross-product interaction of all pairwise task and technology characteristics. To assess the impact of TTF, continuous moderator effects were also modelled using the PLS-SEM product indicator approach to create interaction terms (Hair et al., 2014). This Moderation 'fit' perspective was extended by examining TTF for non-linear effects on mHealth tool use and CHW performance, using Response Surface Methodology with Polynomial Regression (Edwards, 2002). In Chapter 8, the adoption and use of the Fit as Mediation perspective (Venkatraman, 1989, p. 428) to examine the ‘fit’ between the CHW task and mHealth tool characteristics (TTF) and its effects on use and user performance, is described. This ‘fit’ was operationalized as a perceived intervening mechanism between antecedent CHW task and mHealth tool characteristics and consequent use and user performance outcomes. To assess the impact of TTF, PLS-SEM mediator analysis with bootstrapping was used (Hair et al., 2014, p. 219). In Chapter 9, the adoption and use of the Fit as Covariation perspective (Venkatraman, 1989, p. 435) to examine the ‘fit’ between the CHW task and mHealth tool characteristics (TTF) and its effects on use and user performance, is described. This ‘fit’ was operationalized as an observed pattern of co-aligned and internally consistent CHW task and mHealth tool characteristics. To assess the impact of TTF, PLS-SEM (Hair et al., 2014) was used to model ‘fit’ as a reflective first-order reflective second-order construct (Jarvis, Mackenzie and Podsakoff, 2003, p. 205).

In Chapter 10, the examination of the impacts of (1) mHealth tool use on CHW performance, (2) perceived TTF on mHealth tool use and CHW performance, and (3) precursors of use on mHealth tool use, including the use of PLS-SEM mediator analysis with bootstrapping (Hair et al., 2014), is described. In doing so, determinants of use and user performance in addition to TTF, were examined. In addition, the intervening role of use between precursors and user performance was considered.

In Chapter 11, the present study is concluded. A summary of the study is provided and limitations in research design are highlighted. Subsequently, study contributions to theory, methodology, practice, and context, are described, and implications for future research are derived.

A number of thesis chapters have already been published. The thesis publications are listed in Table 1.3. In all instances, the published papers have been re-formatted and updated for inclusion in this thesis.

Table 1.2. Thesis Publications	
Thesis Component	Publication
Abstract	Gatara (2013) 'Mobile Technology-Enabled Healthcare Service Delivery Systems for Community Health Workers in Kenya: A Technology-to-Performance Chain Perspective', Journal for Health Informatics in Africa (JHIA) vol.1, no. 1, pp. 179-180. This paper was also part of proceedings of the 8th Health Informatics in Health Informatics in Africa Conference (HELINA), Nairobi, Kenya).
5	Gatara, M. and Cohen, J.F (2015) Mobile Health Tool Use and Community Health Worker Performance: A Quasi-Experimental Post-Test Perspective, Journal for Health Informatics in Africa (JHIA), vol. 2, no.2, pp. 44-54. This paper was also part of proceedings of the 9th Health Informatics in Africa Conference (HELINA), Accra, Ghana.
6	Gatara, M. and Cohen, J.F (2015) 'Matching Task and Technology Characteristics to Predict mHealth Tool Use and User Performance', A Study of Community Health Workers in the Kenyan Context', Proceedings of the 8th International Conference on Health Informatics (HEALTHINF), Lisbon, Portugal, pp. 454-461.
8	Gatara, M. and Cohen, J.F (2014) 'The Mediating Effect of Task-Technology Fit on mHealth Tool Use and Community Health Worker Performance in the Kenyan Context', Proceedings of the 8th International Development Informatics Association Conference, Port Elizabeth, South Africa, pp. 323-336.
9	Gatara, M. and Cohen, J.F. (2014) 'Mobile-Health Tool Use and Community Health Worker Performance in the Kenyan Context: A Task-Technology Fit Perspective', Proceedings of the Southern African Institute for Computer Scientists and Information Technologists (SAICSIT) Annual Conference 2014, Pretoria, South Africa, pp. 1-10.
6 to 9	Gatara, M. (2016) 'Mobile Health Tool Use and Community Health Worker Performance in the Kenyan Context: A Comparison of Task-Technology Fit Perspectives, In mHealth Ecosystems and Social Networks in Healthcare, Lazakidou, A.A., Zimeras, S., Iliopoulou, D. and Koutsouris, D. [Eds.], Springer, pp. 55 – 78.

2 Contextual Background

2.1 Introduction

In the developing world, expanding networks and decreasing costs have contributed to the proliferation of emerging mobile technologies (Jan, Mohutsiwa-Dibe and Loukanova, 2014). These technologies could enable service delivery in the sectors of governance (Ntaliani, Costopoulou and Karestos, 2008), education (Ally, 2009), finance (Ngugi, Pelowski and Ogembo, 2010), and health (Mechael, 2009). In the health sector particularly, the use of mobile technologies to enhance patient care delivery has emerged as a key priority for sustainable development (Zambrano and Seward, 2012).

In this chapter, the underlying contextual background of the present study is discussed. The existing literature on (1) mobile health (mHealth) and (2) community health work, is reviewed. First, mHealth applications are identified and examples provided. Second, mHealth projects in which these applications are used are identified. Third, shortcomings in research on mHealth (1) applications and (2) projects, are identified. Fourth, the role and responsibilities of Community Health Workers (CHWs) are discussed. Fifth, the use of mHealth tools by CHWs is discussed. Sixth, shortcomings in research on (1) CHWs and (2) CHW mHealth tool use, are discussed.

The mobile technology-enabled support of health service delivery is discussed in Section 2.2.

2.2 An Overview of Mobile Health (mHealth)

'Mobile-health' or 'mHealth' is the use of mobile technologies to support service delivery within healthcare systems (Mechael, 2009; van Heerden, Tomlinson and Swartz, 2012). The concept of mHealth is informed by two distinct perspectives (Mechael, 2009; Leon and Schneider, 2012). First, mHealth can be viewed as a subset or extension of 'electronic health' or 'eHealth', the use of Information and Communication Technologies (ICTs) to support healthcare delivery. Second, mHealth can be described as a 'mobile service' or 'mService'. In the present study, mHealth is understood to be the intersection between mobile technologies and healthcare systems, as depicted in Figure 2.1.

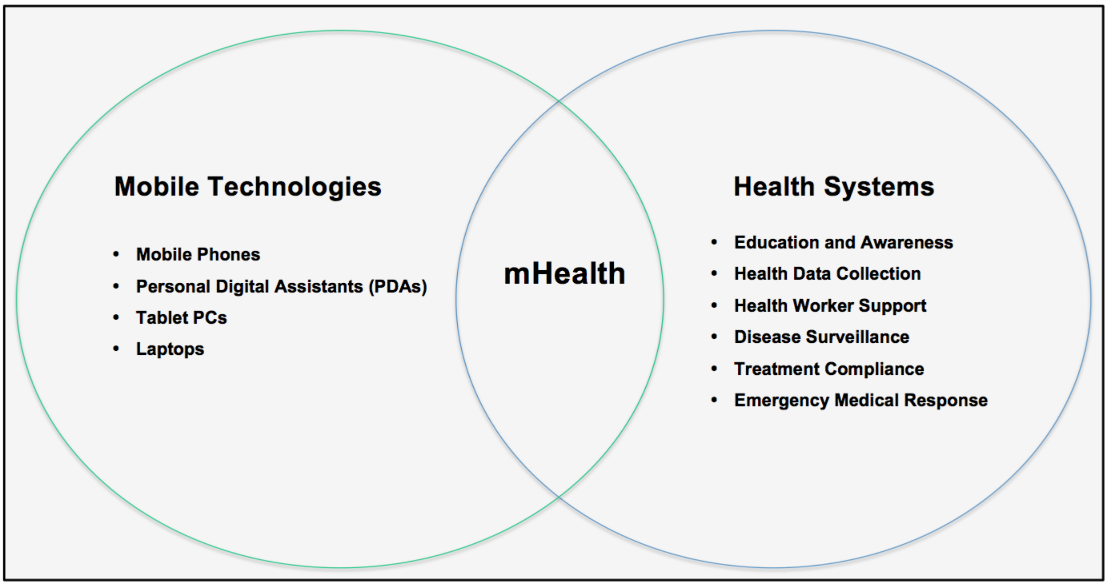

Figure 2.1. The Intersection between Mobile Technologies and Healthcare Systems

If applied correctly, mHealth could enable the delivery of care to underserved populations and contribute to improving disease prevention efforts (World Health Organization, 2010). This could ameliorate the lack of timely and actionable surveillance and slow down rates of information flow occasioned by reporting delays (LeMaire, 2011, p. 10). To understand the importance of mHealth, it is important to first recognize its various applications, especially in low-resource developing country settings. There are six typical mHealth applications, as discussed in Section 2.3.

2.3 Mobile-Health (mHealth) Applications

Numerous mobile technologies have been designed to support various healthcare initiatives in the developing world. These technologies can be grouped into the following categories of mHealth applications.

1. Education and Awareness
2. Health Data Collection
3. Health Worker Support
4. Disease Surveillance
5. Treatment Compliance
6. Emergency Medical Response

First, mHealth applications have been used to educate communities and create awareness.

2.3.1 Education and Awareness

The prevention of infectious diseases is less costly than treatment (Earth Institute, 2010). Consequently, more emphasis is now being placed on disease prevention. Diseases impose great economic burdens on society, making prevention efforts a worthwhile investment globally. This is especially the case in low-resource settings where infectious diseases and chronic conditions put a strain on existing healthcare infrastructure (p. 36). To counteract this, the World Health Organization (WHO) identified three steps to ensuring more effective preventive patient care (Earth Institute, 2010, p. 36). These steps are (1) providing integrated preventive healthcare, (2) promoting financing systems and policies to support preventive healthcare, and (3) prioritizing preventive healthcare as a key component of every intervention. Unfortunately, service delivery is not often aimed at preventive care. Moreover, persuading patients to adopt healthier lifestyles poses a challenge (World Health Organization, 2008). In low-resource settings the rapid adoption of mobile technologies present numerous opportunities to enhance preventive care. For example, Short Message Service (SMS) messages could be transmitted to patients to promote smoking cessation (Earth Institute, 2010). In a study conducted of a low-income HIV-positive population, it was reported that respondents were equipped with free mobile handsets through which they received counselling. Findings indicated that 75% of participants abstained and 95% attempted to quit smoking (Lazev, Vidrine, Arduino and Gritz, 2004). A typical case of an mHealth application for education and awareness is highlighted in Box 2.1.

Box 2.1: mHealth Application for Education and Awareness

'Text to Change' is an NGO that deploys mobile phones in an effort to enhance HIV/AIDS sensitization and prevention efforts in Uganda. It is part of a pilot project devised to scale up Voluntary Counseling and Testing (VCT), influence behavioural change through civic education, and monitor and evaluate HIV/AIDS prevention. Text to Change spearheaded the development of interactive multiple-choice quizzes to improve HIV/AIDS knowledge and awareness. Questions were sent through SMS to 15,000 mobile phone subscribers in the Greater Mbarara region. Over a three-month period from February to April of 2008, 2,610 out of 15,000 mobile phone users responded to these questions (Earth Institute, 2010). Some questions elicited more frequent responses than others. For instance, a question on 'the accuracy of HIV tests' elicited responses from approximately 2,500 participants. In comparison, a question on the 'presence of HIV in body fluids', elicited responses from between 1,000 and 1,500 participants (Earth Institute, 2010, p. 42).

Source(s): (Earth Institute, 2010, p. 42)

Second, mHealth applications have been used to support data collection for patient care.

2.3.2 Health Data Collection

The collection of disease data in real-time can dramatically reduce morbidity and mortality (Earth Institute, 2010). The analysis of this data can impact the speed at which treatment reaches patients in low-resource settings. However, health data collection has often proven cumbersome due to the use of traditional paper-based systems (p. 22). The use of mobile technologies for data collection can resolve this. For instance, adopting mHealth tools over paper-based systems can significantly reduce data collection error rates (Earth Institute, 2010). In a study of health surveys in Gambia, it was observed that respondents using Personal Digital Assistants (PDAs) to collect malaria data reported error rates of between 0.1% and 0.6%, which indicated improved accuracy over paper-based forms (Forster, Behrens, Campbell and Byass, 1991). A typical case of an mHealth application for the collection of health data is highlighted in Box 2.2.

Box 2.2: mHealth Application for Data Collection

> 'EpiHandy', is a health data collection and record access system sponsored by the Centre for International Health in Norway, enabled by mobile devices to help mitigate the high costs and inefficiencies of large-scale paper-based surveys. Despite its deployment in various countries since its launch in 2003, it has largely been used in Uganda, Zambia, and Burkina Faso. For instance, in Uganda, mobile phones were deployed to participating clinics and public health experts trained the local staff on using its open source 'JavaRosa' software to complete and submit filled medical forms. The data on these forms were transmitted through services made available on the local mobile network. EpiHandy has yielded positive results during a 5-year assessment in which 14 interviewers collected information on breastfeeding habits and child anthropometry in rural Eastern Uganda. Notable outcomes of this initiative include a reduction in data entry errors and improved cost effectiveness over paper-based surveys.

Source(s): (Vital Wave Consulting, 2009)

Third, mHealth applications have been used by field health workers for decision-support.

2.3.3 Support for Health Workers

The use of mobile technologies by field health workers can be used as decision support tools at the point-of-care or as an enabler of access to information (Earth Institute, 2010). For instance, nurses in Dangme West, Ghana, have used mobile phones to consult senior medical colleagues on handling complex maternal and newborn cases (Mechael, 2009). In

Cameroon, it was similarly observed that resident medical students used mobile phones to consult their supervisors through voice and SMS whilst completing their training in a rural setting (Scott, Ndumbe and Wootton, 2005). A typical case of an mHealth application for health worker support is highlighted in Box 2.3.

Box 2.3: mHealth Application for Health Worker Support

The Ugandan Health Information Network (UHIN), an initiative sponsored by Uganda Chartered HealthNet (UCH), AED-SATELLIFE, Makerere University Medical School, Connectivity Africa, and the International Development Research Centre (IDRC) used PDAs to provide medical education services to health personnel in Uganda. The PDAs transmitted messages via infrared beams transmitting signals to battery operated access points. The program was launched in 2003, and so far 350 PDAs connected to 20 access points in various districts in Uganda have been used. Health workers now using these devices have reported improved job satisfaction and staff retention.

Source(s): (Vital Wave Consulting, 2009)

Fourth, mHealth applications have been used by field health workers for disease surveillance.

2.3.4 Disease Surveillance

The use of mobile technologies for disease surveillance and reporting at the point-of- care could contribute to more integrated health systems. This is aided by the use of mobile devices to detect epidemics early (Earth Institute, 2010). Mobile technologies offer the added advantage of providing accurate data for the effective delivery of patient care (p. 22). Uses of mobile technologies for disease surveillance have been cited (Earth Institute, 2010). For example, in a ten-day field study conducted to facilitate effective patient follow-ups in Mozambique, Global Positioning System (GPS)-enabled mobile phones were used to map 4,855 households across 32 villages in 8 districts (Krishnamurthy, Frolov, Wolkom, Vanden and Hightower 2006). A typical case of an mHealth application for real-time disease surveillance is highlighted in Box 2.4.

Box 2.4: mHealth Application for Disease Surveillance

The 'Tamil Nadu Health Watch', sponsored by 'Voxiva', was a phone-based disease surveillance platform deployed in India's hard-hit Tamil Nadu State. The platform, launched in May 2005, supported field workers to relay disease incidence data to health officials in real time. As part of this initiative, Voxiva was used to train over 300 primary health centre doctors. This was achieved through interactive sessions conducted with local authorities to promote and reinforce outbreak surveillance.

Source(s): (Vital Wave Consulting, 2009)

Fifth, mHealth applications have been used to facilitate treatment compliance among patients.

2.3.5 Treatment Compliance

Treatment compliance involves the adherence of patients to medication. For instance, patients must adhere to prescribed antibiotics used to treat tuberculosis or anti-retroviral therapy for HIV/AIDS (Earth Institute, 2010). Mobile technologies could enable treatment compliance (p. 14). Uses of mobile technologies for treatment compliance have been cited (Earth Institute, 2010). For instance, in a study of 31 HIV patients in Peru, it was reported that mobile phone use significantly improved their adherence to anti-retroviral treatment (Curioso and Kurth, 2007). A typical case of an mHealth application for treatment compliance is highlighted in Box 2.5.

Box 2.5: mHealth Application for Treatment Compliance

'SIMpill' is a solution designed to help improve TB treatment compliance through the attachment of a SIM card and transmitter to pill bottles. When a patient opens one, an SMS message is sent to the nearest health worker. If it is not opened as expected, the patient receives an SMS reminder to take his or her medication. If the patient fails to comply, the health worker is prompted to call or visit the patient to encourage medication adherence. Following a 2007 pilot study conducted in South Africa to test system efficacy, it was reported that 90% of patients using 'SIMpill' complied with their medication regimen.

(Source: Vital Wave Consulting, 2009)

Sixth, mHealth platforms have been used to support prompt responses to medical emergencies.

2.3.6 Emergency Medical Response Systems

In low-resource settings, Emergency Medical Response Systems (EMRSs) are not often prioritized (Earth Institute, 2010). This has been attributed to the prohibitive costs of transportation and advanced clinical care (Kobusingye, Hyder, Bisha, Hicks, Mock and Joshipura, 2005). The use of mobile devices as EMRSs is a simple and effective solution to these prohibitions (Earth Institute, 2010). During emergencies, mobile technologies can facilitate human resource support, transport and communications, patient transfers, and disaster planning (p. 45). The use of mobile phones as EMRSs in low-resource settings has been cited (Earth Institute, 2010). For example, in a study in Egypt it was reported that during emergencies, participants preferred using mobile phones to hire transport because their calls were routed to a call centre thereby reducing response times (Mechael, 2006). A typical case of an mHealth application for emergency medical responses is highlighted in Box 2.6.

Box 2.6: mHealth Application for Emergency Medical Responses

'Alerta DISAMAR', is a multi-platform emergency alert system deployed in Peru and supported by the US Navy. The system allows users to transmit or access data using multiple technologies, including mobile phones and the Internet. Alerts of disease outbreaks are sent as text, voice, and e-mail messages. Following an evaluation of the project conducted in 2003, it was found that within the first year of deployment, disease outbreak responses in remote areas were improved. Since its launch, the system has been used to report more than 80,500 health cases of diphtheria, yellow fever, snakebites, diarrhoea, and acute respiratory infection.

(Source: May et al., 2009; Vital Wave Consulting, 2009)

In summary, a review of the existing literature indicates that mHealth applications could enhance preventive care by promoting healthy patient behaviour (Ladzev et al., 2004). In addition, mHealth applications could improve data collection by reducing error rates (Yu et al., 2009). Moreover, mHealth applications could facilitate consultation between field workers and health professionals on complex medical cases (Mechael, 2009). Furthermore, GPS-enabled mHealth applications could facilitate the mapping of households for disease monitoring (Krishnamurthy et al., 2006), treatment compliance through SMS adherence reminders transmitted to patients (Curioso et al., 2009), and emergency interventions for timely access to medical care (Mechael, 2006). It is important to recognize that the applications identified can be tools used as part of developing country mHealth projects. Examples of mHealth projects in the aforementioned application categories are provided in Table 2.1.

Table 2.1. mHealth Projects in Developing Countries

Category	Project	Intervention	Country
Education and Awareness	Project Masiluleke	Send SMS messages to encourage HIV/AIDS testing and treatment.	South Africa
	SMS for Health	Promote HIV prevention through an SMS Quiz.	Uganda
	Learning About Living	Promote learning about HIV/AIDS through question and answer platform.	Nigeria
Health Data Collection	EpiHandy	Collect data and access patient	Uganda,

		records enabled by PDAs.	Zambia, Burkina Faso
	EpiSurveyor	Create, share, and deploy health surveys and forms on mobile devices.	Kenya, Uganda, Zambia
	Pesinet	Use of a mobile application collect and transfer child health data.	Mali
	Uganda Health Information Network (UHIN)	Use of PDAs to collect health data and provide medical information to physicians.	Uganda
	Mobile E-IMCI	Use of PDAs to promote health worker adherence to Integrated Management of Childhood Illness (IMCI) protocols.	Tanzania
Disease Surveillance	GATHER	Use of data entry tools for weekly disease surveillance for 20 health clinics.	Uganda
	Remote Interaction, Consultation, and Epidemiology (RICE)	Use of a mobile platform for tracking and early detection of communicable diseases.	Vietnam
	Tamil Nadu Health Watch	Use of mobile phones to report disease incidence data to health officials in real time.	India
Treatment Compliance	Cell-Life	Use of data-enabled mobile phones to record HIV/AIDS patient details such medication adherence.	South Africa
	SIMpill	Sending SMS messages to health workers monitoring TB patient medication adherence.	South Africa
Emergency Medical Responses	Alerta DISAMAR	Use of mobile technologies to transmit and access data for rapid disease outbreak reporting.	Peru

Source(s): Vital Wave Consulting (2009); LeMaire (2011)

The significance of implementing mHealth projects in low-resource settings is discussed in Section 2.4.

2.4 Mobile-Health (mHealth) Projects

As evidenced by Table 2.1, several mHealth projects have been implemented in developing countries, particularly in Africa. Unfortunately, despite the promise of mHealth, many of these projects are unsustainable and often expire once initial funding has been exhausted. For instance, in Uganda, 23 mHealth projects implemented between

2008 and 2009 did not scale-up[9] beyond the pilot phase (LeMaire, 2011). Similarly, In India, over 30 mHealth pilot projects implemented in 2009 did not scale-up (p. 12). Existing mHealth policies, models and funding schemes have influenced this proliferation of pilot projects without enabling their meaningful and replicable scale-up. LeMaire (2011) evaluated developing country mHealth projects and identified key elements useful for successful scaling-up. There are three elements that inform the present study. First, mHealth projects must be tailored to local contexts to best serve population needs in specific settings. The assessment of local conditions such as typical work practices would contribute to the successful scale-up of these projects. In other words, the mHealth tools used must fit the CHW tasks performed. Second, implementers must devise useful metrics that can be integrated into pilot projects to form a sound basis for the evaluation of mHealth impacts (Mechael, 2009). As such, CHW performance outcomes must be quantified. Third, key stakeholders should be involved in mHealth project design. For instance, engaging potential end-users such as health workers would influence the successful uptake of mHealth tools. In essence, CHW perspectives of task-fit and their use of mHealth tools and facilitating conditions need to be understood. To support the scale-up of mHealth projects, global donors have encouraged research on the use of mHealth platforms in developing countries (Qiang, Yamaichi, Hausman and Altman, 2011). In Section 2.3, examples of applications and benefits of mHealth in low-resource settings were cited. Subsequently, it was established that these are tools used in implemented mHealth projects. Examples of mHealth projects implemented in developing countries were provided. Whereas elements for the scale-up of mHealth projects cited in existing literature were discussed in Section 2.4, there is little or no evidence of mHealth tool impacts on the performance of CHWs in the delivery of patient care. These shortcomings in mHealth research are discussed further in Section 2.5.

2.5 Shortcomings in Prior mHealth Research

In Section 2.3, a number of mHealth applications cited in the literature were identified. These are tools used in various contexts across multiple settings. In prior mHealth research, the possible uses and benefits of these tools have often been cited. However, it must be recognized that the use of these tools is an essential component of mHealth

[9] The term scale-up has been described as the replication of technology in multiple contexts and the large-scale implementation or expansion of mHealth projects in line with national health agendas (LeMaire, 2011; 2013).

projects. In Section 2.4, mHealth projects for low-resource developing countries were discussed. In prior research, conditions for scale-up of mHealth projects are often cited. However, there is a lack of evidence of what factors may contribute to this scale-up of mHealth projects. Specifically, empirical evidence of mHealth impacts on the delivery of patient care is lacking (Mburu, Franz and Springer, 2013; Mburu, 2014). Furthermore, there is an absence of robust frameworks with which to evaluate these impacts. This continues to hamper opportunities to scale-up mHealth projects sustainably (Tomlinson et al., 2013). Scholars have proposed steps that could be followed to ensure the design of more rigorous mHealth studies (Flay, Biglan, Boruch, Castro, Gottfredson et al., 2005). Notably, it has been observed that evidence-based health studies must be underpinned by validated theories of end-user behaviour (Fishbein, Bandura, Triandis, Kanfer, Becker et al., 2000). In addition, the Multi-Phase Optimization Strategy (MOST) has been cited as an example of a systematic approach to the evaluation of health projects (Collins, Baker, Mermelstein, Piper, Jorenby et al., 2011). This strategy comprises two useful components. First, features that contribute to variations in particular interventions must be described. To achieve this, a small core set of key constructs or factors must be identified for observation. Second, multi-factorial designs or multi-variate methodologies must be used to empirically test the effects of these constructs. This systematized evaluation of mHealth impacts is lacking in prior research. In prior works, researchers tend to cite mHealth consequences such as improved accuracy and patient care, but neither qualify nor quantify what factors precipitate these outcomes (Earth Institute, 2010). Moreover, in prior works, mHealth tool end-users are hardly recognized as key contributors to patient care. In addition, the research designs used in prior studies often inform non-replicable feasibility studies in which relatively small sample sizes are used (Earth Institute, 2010). Thus there is a need for studies designed for the comprehensive evaluation of mHealth impacts on end-user behaviour (Prgomet et al., 2009). This can be ensured in a number of ways. First, replicable study designs must be devised to guide research on mHealth impacts. Second, large sample sizes must be used to conduct research on these impacts. Third, the impacts of the mHealth tool on user performance must be evaluated (Earth Institute 2010; Singh and Sullivan, 2011; Tomlinson et al., 2013; Philbrick, 2013).

Despite a growing knowledge repository, policymakers need robust evidence but unfortunately the methods of past studies do not ensure statistically significant results that would meaningfully inform the uptake of mHealth in low-resource developing country settings. Consequently, it becomes more difficult to inform mHealth project planning and implementation (Earth Institute, 2010). This lack of meaningful evidence-based mHealth research is propagated by the persistent use of qualitative designs such as ethnographic methods and interviews. This is indicative of a growing need for more quantitative research designs (Earth Institute, 2010). The use of more rigorous methodologies would benefit mHealth research in two ways. First, evidence would be a product of robust quantitative analysis signifying a data-driven approach to evaluating mHealth impacts. Second, appropriate indicators with which to evaluate mHealth performance impacts can be devised. Scholars in the field of mHealth must also employ robust indicators with which to compare interventions in different patient care settings (Duan et al., 2007). Thus it is important for researchers and practitioners to reach consensus on what study designs, methods, and measures are appropriate for evaluating mHealth impacts in low-resource settings (Earth Institute, 2010).

In summary, mHealth research shortcomings identified indicate that (1) there is a need for evidence of mHealth tool impacts on end-user behaviour such as performance in the delivery of patient care (Prgomet et a., 2009), (2) quantitative multi-factorial designs or multi-variate methodologies with multi-variate analysis must be used to evaluate these impacts (Collins et al., 2011; Philbrick, 2013) (3) researchers must conduct evidence-based research underpinned by validated theories of end-user behaviour (Fishbein et al., 2000), and (4) replicable study designs with large sample sizes must be used (Earth Institute, 2010; Tomlinson et al., 2013).

The present study is informed by two integral components of mHealth projects implemented in low-resource developing country settings. First, the mHealth tool is the technology used by the end-user to deliver patient care. Second, the mHealth tool end-user must be a health worker entrusted with the responsibility of delivering patient care in a community setting. Consequently, in the present study, the extension of mHealth to community health work is particularly important. Specifically, research is needed on how to support the health worker through mHealth tool use at the point-of-care. Therefore a distinction must be made between two mHealth project typologies. First, there have been several general-purpose mHealth projects. Second, there are considerably fewer mHealth projects extended to community health work. Prior mHealth research is often skewed in favour of broader mHealth tool use contexts. Thus more specific research on mHealth for community health work is lacking. To link mHealth to community health work, it is important to first identify and recognize the role of the health worker tasked with the delivery of patient care. The component of community health work is discussed in Section 2.6.

2.6 The Community Health Worker (CHW)

2.6.1 Community Health Workers (CHWs) and the Formal Care System

Community Health Workers (CHWs) are often the only link to patient care for millions of people in the developing world (Liu et al., 2011). They are often the first point of contact with the formal care system (Global Health Workforce Alliance, 2010), acting as a bridge between their communities and hospitals or clinics (World Health Organization, 2006). Consequently, CHWs represent the intersection between two dynamic and overlapping systems (Naimoli, Frymus, Quain and Roseman, 2012) as depicted in Figure 2.2.

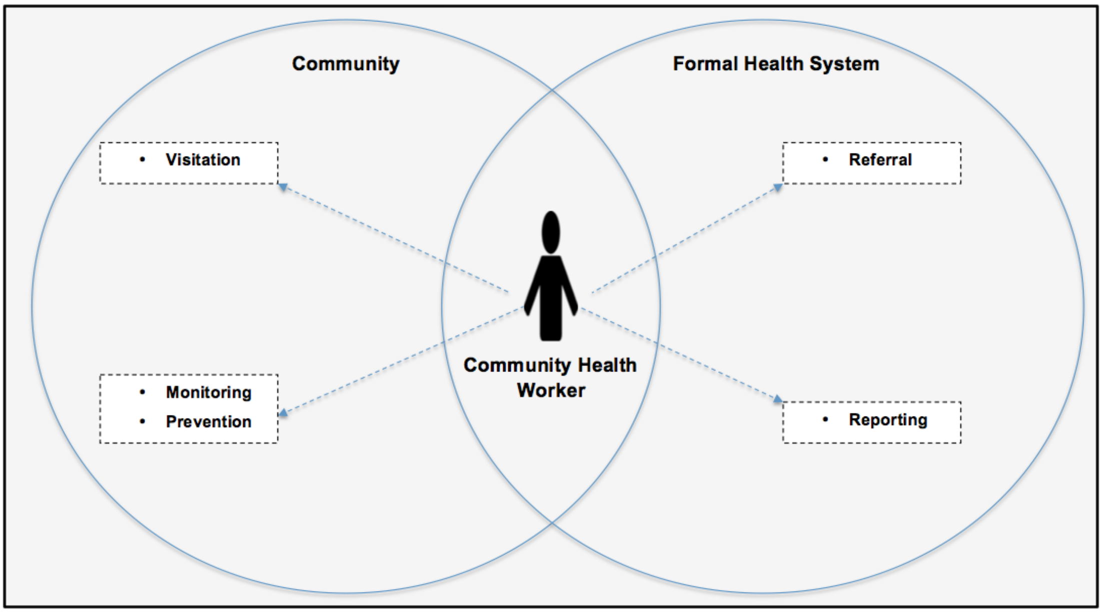

Figure 2.2. The Intersection between the Community and Formal Health System

There are five primary responsibilities of CHWs deployed to serve patients in households. These are the responsibilities of (1) visitation, (2) monitoring, (3) prevention, (4) referral, and (5) reporting. First, CHWs routinely visit households to collect health data and deliver care to patients who would otherwise be unreachable (DeRenzi et al., 2012). In visiting households, they offer an entry point for the delivery of patient care (Braun et al., 2013) by performing the tasks of monitoring, prevention, and referral (Burket, 2006;

Partners in Health, 2011, Liu et al., 2011). Second, CHWs monitor households when conducting real-time disease surveillance (Braun et al., 2013) and observing patients for treatment compliance (Earth Institute, 2010). Examples of monitoring include assessing mother and child nutrition, detecting diarrhoea symptoms and fever and malaria signs, observing HIV/AIDS and TB patients, conducting birth registration, evaluating usage of bed nets, and collecting health data from patients (Bhutta, Darmstadt, Hasan and Haws, 2005; Bryce Black, Walker, Bhutta, Lawn and Steketee, 2005; Adudans, Wariero, Wendo and Barasa, 2013). Third, CHWs exercise prevention to promote health initiatives to mitigate against disease (Singh and Sullivan, 2011). Examples of prevention include educating patients on water treatment and hygiene, advocating for HIV testing, promoting immunization, re-stocking condoms and contraceptive pills, installing insecticide-treated nets for malaria, and administering oral rehydration therapy (Conway et al., 2007; Haines, Sanders, Lehmann, Rowe, Lawn, Jan, Walker and Bhutta, 2007; World Health Organization, 2006; Peterson, 2008; Adudans et al., 2013). Fourth, CHWs refer patients to hospitals and clinics for further care or treatment (Liu et al., 2011). Examples of referral include cases of children with oedema and severe weight loss symptoms, febrile infants under 5 years at risk of fever and malaria, couples who need advice on long-term family planning methods, and mothers who seek maternal care (Singh and Sullivan, 2011; Adudans et al., 2013). Fifth, CHWs are expected to routinely report their household visitations. In addition, they are required to report on monitoring, promotion, and referral tasks that they perform in the delivery of patient care. This is effected through the transfer or submission of health data from households to hospitals or clinics (DeRenzi et al., 2011; DeRenzi et al., 2012; Otieno, 2012).

In summary, the community health work literature indicates that typically, CHWs visit patients in households (Earth Institute, 2011), monitor sickness and treatment compliance (Perry and Zulliger, 2012), take preventive measures to mitigate against diseases (Bhutta et al., 2010), and refer patients to hospitals and clinics for advanced care or treatment (Liu et al., 2011). In addition, CHWs are expected to report on their household visitations, and the monitoring, prevention, and referral tasks that they perform (Bhutta et al., 2005; Haines et al., 2007; Braun et al., 2013). These are the responsibilities that encompass tasks that underscore the importance of CHWs to the delivery of patient care in low-resource settings. Thus the importance of CHWs to the developing world must be recognized.

2.6.2 Community Health Workers in the Developing World

In developing countries, it has been reported that there is a shortage of 2.3 million doctors, nurses, and midwives, and in excess of 4 million health workers overall. Moreover, in Europe for instance, 173,000 doctors are trained every year, compared to only 5,100 in Africa. By providing basic low-cost healthcare and services to these populations, CHWs represent a solution to this shortfall in global health workers (Conway, Gupta and Khajavi, 2007). Furthermore, of the world's seven billion people, one billion will never formally seek patient care. Of these people, 350 million are children (Dalberg Global Development Advisors, 2012, p. 11). Consequently, underserved populations in low-resource settings have become more dependent on CHWs for primary healthcare services (Liu et al., 2011). For additional insight, recent estimated numbers of CHWs deployed[10] in several developing African countries are provided in Table 2.2. The CHWs deployed in these developing countries typically operate within low-resource settings.

Table 2.2. Community Health Workers (CHWs) in Developing Countries

Country	Number of CHWs	Household Coverage	Population Coverage
Mali	698	1000 - 2500	1,302,455
Zambia	50,460	250 - 500	28,065,000
Malawi	12,207	500 -1000	12,237,153
Kenya	22,675	25 - 100	4,811,075
Rwanda	83,476	50 - 100	19,370,155
Ethiopia	41,490	500 - 1000	8,549,547
Senegal	2,301	50 - 100	1,155,000
Ghana	4,517	75 - 100	3,418,643
Nigeria	7,107	2500-3500	5,362,904
Congo (DRC)	4,696	100 - 500	352,200
Niger	3,056	100-250	21,833
Mozambique	4,300	100 - 400	4,750,000
Sierra Leone	3,753	50 - 100	5,129,300
Liberia	9,672	250 - 500	9,375,719

Source(s): One Million Community Health Workers Campaign (2013); (http://1millionhealthworkers.org/operations-room-map/); CCM Central (2014)

[10] There are approximately 322, 199 CHWs deployed in 34 countries in Sub-Saharan Africa, covering an estimated total population of 126, 211, 216 (http://1millionhealthworkers.org/operations-room-map/). The majority of these CHWs (including those in the countries listed in Table 2.2) are not adequately equipped with mHealth tools and have typically relied on paper-based systems.

Notably, training a CHW for a year would cost 2.5% of the equivalent for a doctor and take less than a fifth of the time required (Conway et al., 2007). Whereas clinically skilled personnel contribute to enhanced patient services, CHWs need relatively shorter training to more rapidly provide basic household-level care (Singh and Sullivan, 2011). Of note, a typical CHW is expected to provide care for up to 100 households (Dalberg Global Development Report, 2012). In delivering patient care to households, CHWs have been recognized as significant contributors to Millennium Development Goals (MDGs) 4, 5, and 6 of improving child and maternal health (Earth Institute, 2011). Every year, approximately 8.8 million children die before age 5 and roughly 350,000 women have succumbed to pregnancy or birth-related complications, yet these deaths can be prevented by enabling access to the basic primary care that CHWs could provide (Dalberg Global Development Advisors, 2012). CHWs deployed to households play a crucial role in low-resource settings, thus enhancing their capacity to deliver services to patients is imperative (Perry and Zulliger, 2012). One effective way in which this could be achieved is by equipping them with mHealth tools at the point-of-care (Liu et al., 2011). The integration of these tools into their customary workflows could empower them by enhancing their performance of monitoring, prevention, referral, and reporting tasks (Bhutta et al., 2005; Haines et al., 2007; Braun et al., 2013). In recognizing this opportunity, there is a pertinent need to extend mHealth to community health work.

2.6.3 The Use of mHealth Tools for Community Health Work

The use of mHealth tools is arguably a more immediate and cost-effective way through which CHW-facilitated patient care in low-resource settings could be enhanced (Perry and Zulliger, 2012). These tools would strengthen point-of-care support whilst enabling quicker emergency response times (Mechael, 2009; Singh and Sullivan, 2011, p. 36). Moreover, when referring patients for further care or treatment, CHWs would be able to directly liaise with clinicians or doctors in clinics and hospitals. Furthermore, CHWs would be able to more accurately collect data at the household level (Braun et al., 2013), where the accuracy of this data is important to planning community-based interventions and tracking disease prevalence. A number of trends in CHW mHealth tool use have been cited in the existing literature.

First, researchers have supported the aim of designing mHealth tools that improve CHW workflows (Bernabe-Ortiz, Curioso, Gonzales, Evangelista, Castagnetto et al., 2009; Tomlinson et al., 2009). Second, the use of mHealth tools could facilitate the exchange of information between CHWs and nurses or physicians in hospitals and clinics (Lemay, Sullivan, Jumbe and Perry, 2011). Third, mHealth tool use among CHWs could support health and disease monitoring (Chaiyachati, Loveday, Lorenz, Leash, Larkan, Cinti, Ferdinand and Haberer, 2013). Fourth, mHealth tool use among CHWs could enhance decision support (Arango, Iyengar, Dunn, and Zhang, 2011). Despite these positive trends, there is a need to create strong linkages between mHealth tools and consequences such as (1) improved workflows or (2) CHW performance. Whereas several possible uses of mHealth tools among CHWs have been cited, the most prominent interventions have included health and disease monitoring and data collection (Medhi, Jain, Tewari, Bhavsar, Matheke-Fischer and Cutrell, 2012; Chaiyachati et al., 2013), and the use of job aids for decision support (Arango, Iyengar, Dunn et al., 2011). In precious few prior works, specific consequences of mHealth-enabled CHW interventions are quantified. In these works, mHealth tools have been compared to traditional paper-based systems. For the most part, positive mHealth tool impacts have been confirmed primarily in the area of monitoring in relation to data collection and reporting (DeRenzi et al., 2011; Medhi et al., 2012; Chaiyachati et al., 2013). For instance, in a study on pregnancy monitoring by CHWs in Rwanda, it was reported that there was an increase in facility-based deliveries from 72% to 92% within a year of using an mHealth tool (Ngabo, Nguimfack, Nwalgwe, Mugeni, Muhoza, Wilson, Kalach, Gakuba, Karema and Binagwaho, 2012). Elsewhere, in a study on child healthcare provision by CHWs in Tanzania, it was reported that 85% of cases were successfully monitored using an mHealth tool compared to 65% enabled by a traditional paper-based system (DeRenzi, Parikh, Mitchell, Chemba, Schellenberg, Leash, Sims, Maokola, Hamisi and Borriello, 2008). Similarly, in a study on child health monitoring by CHWs in India, it was reported that on average, mHealth tools reduced the time spent collecting field data from 45 days to 8 hours, increased patient form completion rates from 67% to 84%, and minimized error rates from 9.4% to less than 1% (Medhi, Jain, Tewari, Bhavsar, Matheke-Fisher and Cutrell, 2012).

These and similar past studies on mHealth outcomes in the context of community health work are summarized in Table 2.3.

Table 2.3. Mobile Technology and Community Health Work Studies			
Approach	Intervention	Outcome	Source
Randomized Control	Routine CHW patient visits with and without supervisor involvement.	CommCare mHealth platform generates SMS reminder reducing days patients were overdue by 86%.	DeRenzi et al (2012)
Mixed Methods	The monitoring of patients infected with multi-drug resistant tuberculosis.	Mobilize mHealth platform. increases weekly paper patient forms submitted to 27% (9 of 33) from 5% (14 of 29).	Chaiyachati et al (2013)
Randomized Prospective Crossover Study	Patient care aided by rich media clinical guidelines on a mobile phone.	mHealth platform reduces errors by an average of 33% and increases protocol compliance by 30.18%.	Arango et al (2011)
Semi-Structured Interview(s), Clinical Trial(s)	Child health monitoring.	eIMCI mHealth platform increases case observed in paper-based trial to 84.7% (304 of 359) from 61% (183 of 299).	DeRenzi et al (2008)
System Design and Piloting	Maternal and child health monitoring.	RapidSMS-MCH mHealth platform increases facility-based deliveries, by 27% up from 72% at baseline a year earlier to 92%.	Ngabo et al (2012).
Field Trial	Child health monitoring.	CommCare mHealth platform (i) increases forms filled to 84% from 67%, and (ii) reduced error rate of 9.4% to approach data quality levels near 100%.	Medhi et al (2012)

Despite cited outcomes in these studies, there is no explicit indicator of CHW performance. Instead, mHealth tool impacts are reported as evidence of CHW performance. Specifically, mHealth platform functionality is prioritized with less attention afforded to the technology user, namely the CHW. Consequently, it appears that the mHealth tool takes precedence over its user to whom patient care delivery is entrusted. Thus CHW work has rarely been evaluated in these prior studies (Kallander, Tibenderana, Akpogheneta, Strachan, Hill, ten Asbroek, Conteh, Kirkwood and Meek, 2013). This can be effectively addressed by (1) prioritizing CHW performance and (2) evaluating this performance using an mHealth tool compared to the alternative traditional paper-based system. However, a common set of criteria with which to evaluate CHW performance dimensions is necessary for the effective evaluation of CHW performance.

Despite the outcomes measured above, more specific user performance measures are needed to guide research on CHW mHealth tool use. Instead, mHealth tool indicators are used as performance criteria observed as consequences attributed to the technology. Thus a distinction must be made between comparative studies that signify (1) mHealth tool-focused research to demonstrate functional superiority of the mHealth tool as evidence of CHW performance and (2) CHW-focused research to demonstrate superior performance using the mHealth tool as evidence of mHealth tool impacts. Therefore more studies on CHW performance as evidence of mHealth tool impacts are needed. In prior CHW mHealth studies, the former appears to be more prominent than the latter. Moreover, there is insufficient evidence of how CHWs perceive the contribution of mHealth tools to their performance or evaluate functions of the technology used. These and relative CHW mHealth research shortcomings are expounded in Section 2.7.

2.7 Shortcomings in Prior mHealth Community Health Work Research

In Section 1.6.1, a number of CHW tasks cited in the existing literature were identified. These CHW tasks are performed in low-resource developing country settings. In prior works, examples of these tasks performed at the household level have often been cited. However, the use of mHealth tools to perform these tasks has hardly been evaluated in prior research. Moreover, there is a lack of evidence of what factors influence mHealth tool use. Furthermore, there is little or no evidence of how or why these tools can functionally support CHW tasks. There is a dearth of evidence of how CHW tasks must be evaluated (Lehmann and Sanders, 2007), or what factors contribute to enhancing workflows through task performance (Perry and Zulliger, 2012), yet a potential significant contributor is the use of mHealth tools at the point-of-care. In addition, there is a need for an improved understanding of how to design mHealth tools that better fit CHW tasks to optimize performance (Braun et al., 2013). Consequently, two important steps inform the present study. First, factors must be identified to explain how or why mHealth tool use impacts CHW performance. Second, these factors must be used to evaluate the fit between the CHW tasks performed and mHealth tool used (Perry and Zulliger, 2012; Braun et al., 2013). It is not clear from the existing literature how CHWs equipped with mHealth tools perceive, engage with, or use these technologies. Moreover, there is a lack of evidence of how CHWs evaluate the contribution of mHealth tools to their performance (Kaphle, Chaturvedi, Chaudhuri, Krishnan and Lesh, 2015). Thus there is a need for frameworks with which to evaluate whether mHealth tools are appropriate for and responsive to CHWs (Svoronos, Mjungu, Dhadialla, Luk and Zue, 2010). Despite the role of CHWs as key contributors to primary care, there have been very few studies in which their work practices have been evaluated (UNDP, 2012). The aforementioned shortcomings can be addressed in a number of ways to inform the present study. First, studies to capture the perceptions of CHWs of their work practices must be conducted. Second, researchers must evaluate how CHWs perceive, engage with or use mHealth tools. Third, study findings must be used to explain how CHWs evaluate or perceive mHealth tool impacts on their performance. Lehman and Sanders (2007) observed that researchers have often narrated experiences involving CHWs, thus making a case for their importance, rather than analysing impacts. In existing literature, a set of consistent indicators with which to evaluate CHW performance impacts is lacking. Moreover, the effects of mHealth tool use on CHW performance have rarely been quantified (Lehmann and Sanders, 2007). Furthermore, there is little or no evidence that the causal effects of mHealth tool use on CHW performance have been empirically tested (Braun et al., 2013). Consequently, the use of rigorous methods to evaluate CHW performance impacts is necessary (Jaskiewicz and Tulenko, 2012).

In summary, the shortcomings identified in CHW research indicate that (1) evidence to support the design of mHealth tools that fit CHW task requirements is needed (Braun et al., 2013), (2) robust frameworks and rigorous methodologies must be applied to explain how a fit between CHW tasks and mHealth tools impacts user performance (Svoronos et al., 2010), (3) CHW performance impacts using mHealth tools must be rigorously evaluated (Jaskiewicz and Tulenko, 2012), and (4) the CHW performance effects of mHealth tool use and its determinants must be evaluated (Tomlinson et al., 2013). Notably, in prior research, it appears that CHWs who have been evaluated are not deployed within mHealth projects implemented in low-resource developing country settings. Thus to appreciate the inextricable link between mHealth and community health work, it must be explicitly recognized that the tool user, the CHW, must be an integral component of an implemented mHealth project.

In prior studies, there is an apparent absence of synergy between (1) mHealth tool use (2) mHealth projects, and (3) CHW mHealth tool users. Therefore for the present study, CHW tool users deployed within mHealth projects that are implemented in low-resource developing country settings must be evaluated. Consequently, a number of such projects inform the choice of research setting for the present study.

2.8 Research Setting

The context of the present study is informed by developing world CHW mHealth projects. These are initiatives in which mHealth tools are used by CHWs who visit patients in households and routinely perform the tasks of monitoring, promotion, referral, and reporting. CHWs deployed as part of these mHealth projects could deliver care in a given task category[11]. There are, however, few mHealth projects that explicitly inform CHW delivery of patient care in low-resource settings. For instance, the 'Pesinet' project launched in Mali involves CHWs using mHealth tools to reduce child mortality by enabling access to early treatment (LeMaire, 2011). Similarly, the 'Project Mwana' initiative launched in Zambia involves the use of mHealth tools by CHWs to improve care delivery to mothers and infants in rural settings (Philbrick, 2013). Elsewhere, the 'National Rural Health Mission' project launched in India involves equipping CHWs with mHealth tools used to improve maternal care access (Singh and Sullivan, 2011). These are among notable developing world mHealth projects that involve CHWs using mHealth tools.

[11] In developing world CHW mHealth projects, applications have typically been used for education and awareness, health data collection, health worker support, disease surveillance, treatment compliance, and emergency medical responses.

Table 2.4. Developing Country Community Health Worker (CHW) Mobile-Health (mHealth) Projects			
Project(s)	Intervention	Task	Country
Pesinet	Observe infants for signs of fever, vomiting, diarrhoea, and weight loss.	• Monitoring • Prevention • Reporting	Mali
National Rural Health Mission	Track pregnancies in villages and encourage facility-based delivery.	• Monitoring • Referral • Reporting	India
Nompilo	Providing care by using mobile phones to upload patient data to web servers.	• Reporting	South Africa
Project Mwana	Check up on HIV positive mothers to prevent transmission to infants during birth.	• Monitoring • Referral • Reporting	Zambia, Malawi
Millennium Villages Project (MVP)	Provide maternal and newborn care, check for malaria, malnutrition, and diarrhoea signs, effectively link households to clinics.	• Monitoring • Prevention • Referral • Reporting	**Kenya**, Tanzania, Uganda, Rwanda, Ethiopia, Malawi, Mali, Senegal, Ghana, Nigeria
The Academic Model Providing Access to Healthcare (AMPATH)	Track mothers for pregnancy danger signs, and infants postpartum, collect patient data for decision support and provide rapid feedback.	• Monitoring • Referral • Reporting	**Kenya**
The (mHMtaani) 'Mobile Health for Our Communities' project	Monitor orphans and pregnant mothers, support data gathering and effectively link patients to health facilities.	• Monitoring • Referral • Reporting	**Kenya**

Source(s): Vital Wave Consulting (2009); Svoronos et al (2010); LeMaire (2011); Singh and Sullivan (2011); Adudans et al (2013); Fazen et al (2013); Mkalla (2014)

The implementation of CHW mHealth projects in Kenya informs the context of the present study. Kenya, an emerging developing country, represents an appropriate case for several reasons. First, Kenya has among the highest mobile penetration rates[12] in the developing world (Ngugi, Pelowski and Ogembo, 2010). Second, Kenya is an African leader in mobile technology-enabled innovation (Aker and Mbiti, 2010). Third, Kenya is at the forefront of global mHealth community projects in low-resource developing country settings (LeMaire, 2011). Fourth, Kenya is attractive to international development partners investing in mobile technology-enabled service delivery platforms (Zambrano and Seward, 2012).

[12] According to the most recent statistical report from the Communications Authority of Kenya (CAK), there are 37.8 million subscribers in Kenya, and the mobile penetration rate currently stands at 88% (Communications Authority of Kenya, 2016).

In light of the above, three projects[13] in which CHWs use mHealth tools[14] to deliver patient care inform the present study. The first of these projects, the Millennium Villages Project (MVP) initiative, is described in Box 2.7.

Box 2.7: The Millennium Villages Project (MVP)

The Millennium Villages Project (MVP) was launched in 2005 in Sauri Village, Siaya County, Kenya, and has since expanded through the formation of 13 other village clusters across 10 African countries. These are Dertu (Kenya), Koraro (Ethiopia), Ruhiira (Uganda), Mbola (Tanzania), Gumulira and Mwandama (Malawi), Mayange (Rwanda), Ikaram (Nigeria), Pampaida (Nigeria), Bonsaaso (Ghana), Potou (Senegal), Tiby and Toya (Mali). This was initially part of the now defunct United Nations (UN) Millennium Project, in conjunction with Columbia University's Earth Institute, and 'Millennium Promise' a US-based global non-profit initiative. The MVP, was aligned to Millennium Development Goals (MDGs) 4 and 5, of improving child and maternal health in developing countries. As part of the MVP, CHWs using mobile technologies are deployed to monitor mothers and infants to prevent malaria, malnutrition, and diarrhoea signs, and effectively link them to clinics. Sony Ericsson, MTN, Novartis, the Open Mobile Consortium, the Bill and Melinda Gates Foundation, and the World Health Organization (WHO), sponsored the initiative.

Recently, within the Siaya County (Sauri Village) MVP, 'CommCare', a mobile phone-based open-source application, was used by 120 CHWs to improve disease surveillance, data reporting, and decision support for the monitoring of maternal and child health (Svoronos et al., 2010; Adudans et al., 2013). The CommCare application is installed on smartphones used as mHealth tools by CHWs in Sauri Village, Siaya County. A typical example of the CommCare mHealth tool interface is illustrated in Figure 2.3.

[13] Note: In Kenya, there are not more than approximately 500 deployed CHW mHealth tool users within implemented low-resource setting mHealth projects. As at the time of this study, these were the only officially documented mHealth projects in Kenya. The MOH Division of Community Health Services (DCHS) regulates access to all CHWs in Kenya. CHWs in Kenya have traditionally used Ministry of Health (MOH)-classified paper-based systems.

[14] Similar mHealth technology platforms were used within CHW mHealth projects across identified study sites.

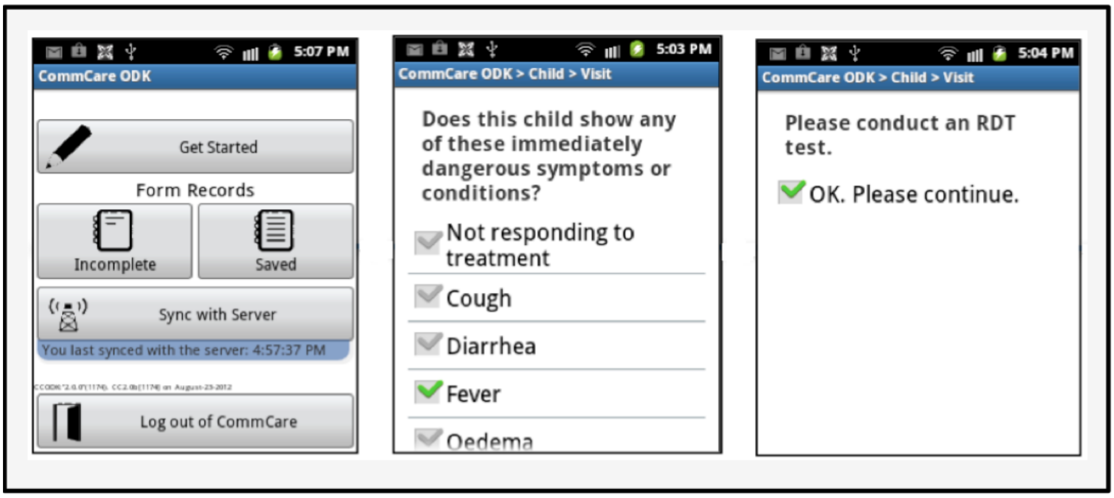

Figure 2.3. CommCare Mobile-Health (mHealth) Tool Interface for the Siaya (Sauri) Implementation

The second project, the Academic Model Providing Access to Healthcare (AMPATH), is described in Box 2.8.

Box 2.8: The Academic Model Providing Access to Healthcare (AMPATH)

The Academic Model Providing Access to Healthcare (AMPATH) project was initiated in 2001, as part of a collaborative effort between Indiana University, Moi University, and the Moi Teaching Referral Hospital. The project was launched to address high maternal and infant mortality in Western Kenya, by supporting innovative approaches to improving maternal, newborn and child health. As part of this initiative, a system was developed for rapid communication between mothers and their care providers, 'The Mother-Baby Health Network', through an mHealth project in Kosirai District, Nandi County, Kenya, implemented to ensure that sustainable maternal and newborn care was provided. The AMPATH, was sponsored by the United States Agency for International Development (USAID), the Bill and Melinda Gates Foundation, and Grand Challenges Canada.

In Nandi County (Kosirai District), Kenya, 92 CHWs were using 'AccessMRS', an open-source Android application loaded on mobile phones and used for maternal and child monitoring, data collection, and reporting (Fazen, Chemwolo, Songok, Ruhl, Kipkoech, Green, Ikemeri, Chritoffersen-Deb, 2013). This application is installed on smartphones used as mHealth tools by CHWs in Kosirai District. A typical example of the AccessMRS mHealth tool interface is illustrated in Figure 2.4.

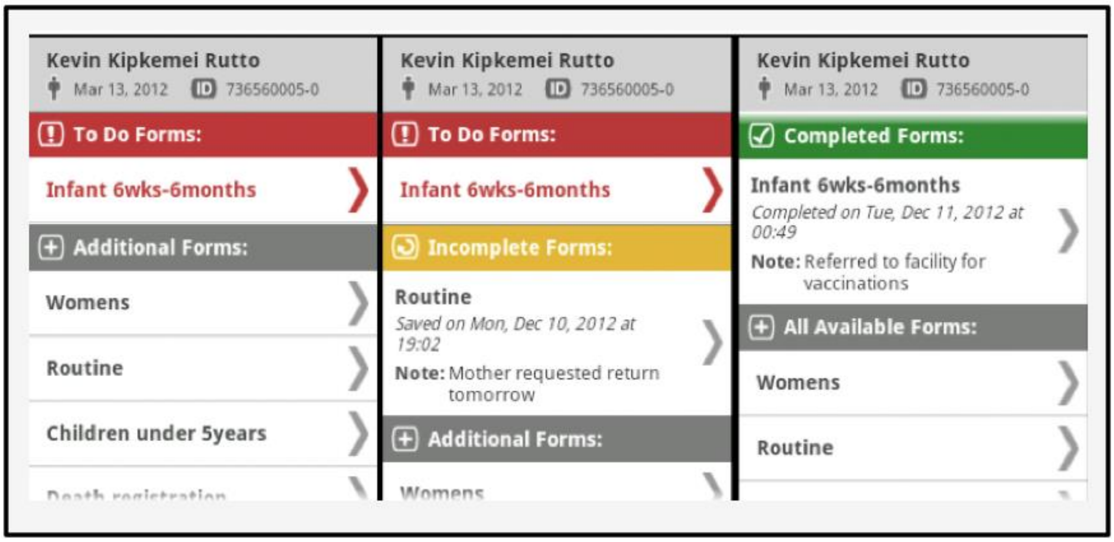

Figure 2.4. AccessMRS Interface Mobile-Health (mHealth) Tool Interface for the Nandi Implementation

The third project, the (mHMtaani) 'Mobile Health for Our Communities' Initiative, is described in Box 2.9.

Box 2.9: mHMtaani 'Mobile Health for Our Communities'

The Mobile Health for Our Communities (mHMtaani) project was initiated in 2013 as part of a collaborative effort between Pathfinder and Dimagi Inc, to support the Aids, Population and Health Integrated Assistance – People Led Universal Sustainability (APHIAplus) initiative. The mHMtaani project was implemented for the sole purpose of enabling high quality patient care at the household level, through the monitoring of antenatal care visits, breastfeeding, and pregnancy danger signs. The mHMtaani project was implemented in six Community Units (CUs) in Kilifi County, Kenya, namely Kaliang'ombe, Dabaso, Jimba, Mtwapa, Shimo la Tewa, and Tsangatsini. The Africa Medical and Research Foundation (AMREF), the United States Agency for International Development (USAID), Visa, and Net Hope, are among notable collaborating project sponsors.

As part of the mHMtaani project in Kilifi, 267 CHWs used the 'CommCare Mobile' platform for decision support and to monitor orphans and pregnant mothers at the household level (Mkalla, 2014). The CommCare Mobile application is installed on smartphones used as mHealth tools by CHWs in Kilifi. A typical example of the CommCare [15] mHealth tool interface is illustrated in Figure 2.5.

[15] A similar 'CommCare' application platform was used by CHWs in the Millennium Villages Project (MVP) in Sauri Village, Siaya County, Kenya.

Figure 2.5. CommCare Mobile-Health (mHealth) Tool Interface for the Kilifi Implementation

The mHealth tool interfaces used at the point-of-care, the counties in which these were applied, the CHW user base, and respective technology platforms, are summarized in Table 2.5.

Table 2.5. Mobile-Health (mHealth Tool) Use Summary

Interface	County	Community Health Worker (CHW) User Base	Platform
CommCare	Siaya	120 CHWs	Open-Source Code Application (Java or Android enabled)
AccessMRS	Nandi	92 CHWs	Open-Source Code Application (Android enabled devices)
CommCare	Kilifi	267 CHWs	Open-Source Code Application (Java or Android enabled)

To demonstrate the impacts of mHealth tool use on CHW performance in low-resource settings, two additional projects are incorporated that were not mHealth projects but instead informed by the use of traditional paper-based systems. The first of these paper-based projects is the Kibera Community Integrated Health Programme initiative, described in Box 2.10.

Box 2.10: The Kibera Community Integrated Health Programme Project

The Kibera Community Integrated Health Programme project was launched in 1998, in Kibera, Nairobi County, Kenya, covering a target population of 35,010 infants below the age of five years, and 43,762 women. In this initiative, maternity nursing clinics, and VCT centres were targeted as outlets for maternal and child care. This project was implemented in four of Kibera's 13 Community Units (CUs), in the areas of Laini Saba, Mashimoni, Silanga, and Soweto East. These units consisted of health facilities such as the Belgian government sponsored Silanga Health Centre. The primary focus of the project was to educate communities on personal hygiene and sanitation, and monitor maternal, newborn and child health to provide care for HIV/AIDS and tuberculosis. The Africa Medical and Research Foundation (AMREF) supported by the European Union (EU) spearheaded this initiative.

In Nairobi County, Kenya, 400 CHWs were deployed as part of the Kibera Community Integrated Health Programme Initiative. The second paper-based project is the Aids, Population and Health Integrated Assistance – People Led Universal Sustainability (APHIAplus) initiative, described in Box 2.11.

Box 2.11: The Aids, Population and Health Integrated Assistance – People Led Universal Sustainability (APHIAplus) Project

The Aids, Population and Health Integrated Assistance – People Led Universal Sustainability (APHIAplus) project, was launched in 2011, in 8 of 14 Counties in the Rift Valley, namely Kenya Narok, Kajiado, Nakuru, Baringo, Laikipia, Elgeyo, Marakwet, Trans Nzoia, and West Pokot. The project was implemented by the Africa Medical and Research Foundation (AMREF), as a lead agency rolling out strategies to improve access to healthcare by supporting data collection at the household level, and strengthening linkages between communities and clinics through effective referral systems. APHIAplus is aligned to the Global Health Initiative (GHI) principles of country led sustainability and integration geared to improving the lives of mothers, children, and their families through HIV/AIDS, tuberculosis, malaria, and reproductive health interventions. As part of the initiative, Community Units (CUs) were established for the sustainable provision of household HIV/AIDS care in collaboration with dispensaries and health centres, by promoting disease prevention through sanitation and hygiene, the monitoring and evaluation of patients, and data reporting for decision support. The initiative is funded by the United States Agency for International Development (USAID) in partnership with AMREF, Family Health International (FHI) 360, Catholic Relief Services (CRS), the National Organization for Peer Educators (NOPE), and Gold Star Kenya.

In Nakuru County, Kenya, 275 CHWs were deployed as part of the APHIAplus initiative. In these two paper-based projects, CHWs deployed to households deliver patient care through the performance of monitoring, prevention, referral, and reporting tasks during household visits.

The CHW deployed in the Counties of Nairobi and Siaya use traditional paper-based systems defined as 'A4 size level 1 data capture tools', which are classified as 'Forms 513-515'. A sample of the 'Ministry of Health (MOH) classified Form 515' is depicted in Figure 2.6.

DISTRICT:... DIVISION:...

NAME OF CU:. .... :............ Total Reported:....

Sno.	Indicators	Total
1	Number of households	
2	Total population	
	Total women 15-49 years	
3	Total children 0- 6 months	
4	Total children under one year old	
5	Total children under five years old	
6	Adolencent and youth - Girls (13 - 24	
7	Adolescent and youth - Boys (13 - 24 years)	
8	Total population of the elderly (60+ years)	
9	Number of household not treating water	
10	Number of households not using ITNs	
11	Number of household without hand washing facilities e.g. leaky tins in use	
12	Number of households without functional latrines	
13	Total pregnant women	
	Number of pregnant mothers who did not attended at least 4+ ANC visits	
14	Number pregnant women referred	
19	Number of children not fully immunized	

Sno	Indicator	
34	Number of deaths	< 1yrs
		1-5 yrs
		Maternal
		Other deaths
		Total deaths
35	**Number of Households without staple food**	
36	**Number of Households without the**	
37	**Number of school drop out**	**Male**
		Female

Remarks ....

Figure 2.6. Ministry of Health (MOH) Form 515 Sample

In the present study, three key projects in which CHWs use mHealth tools to deliver patient care are evaluated. In addition, two projects in which paper-based systems are used are evaluated. Together, five projects[16] inform the context of the present study as mapped in Figure 2.7.

[16] Supported by the Kenya Government through the Ministry of Health (MOH) Division of Community Health Services (DCHS).

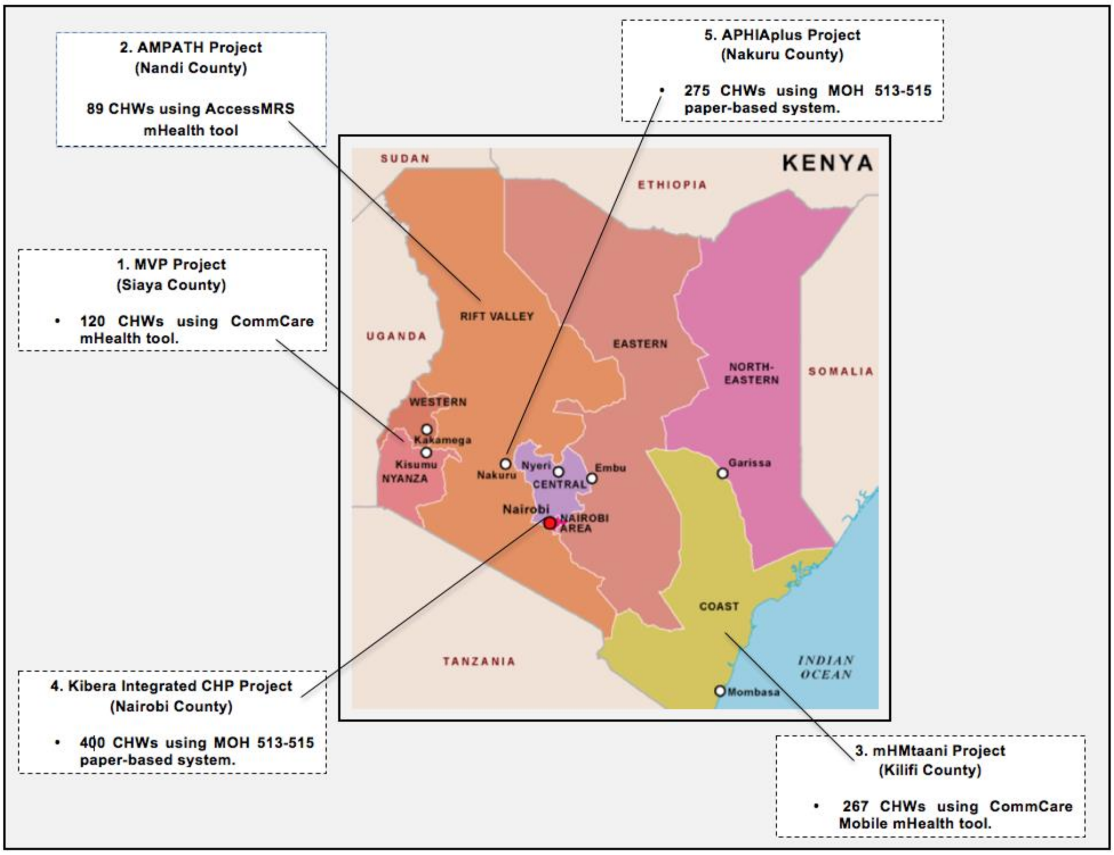

Figure 2.7. Community Project Sites for the Present Study

2.9 Chapter Conclusion

In this chapter, literature on (1) mHealth and (2) community health work was reviewed.

First, six types of mHealth applications (tools) were identified and examples provided. Second, mHealth projects in which these tools are used were identified. Third, shortcomings in research on mHealth (1) applications and (2) projects, were discussed. Fourth, the role and responsibilities of CHWs were identified. Fifth, the use of mHealth tools by CHWs was discussed. Sixth, shortcomings in research on (1) CHWs and (2) mHealth tool use by CHWs, were discussed. The shortcomings identified following a review of literature on (1) mHealth applications, (2) mHealth projects, (3) CHWs, and (4) CHW mHealth tool use, are convergent. Consequently, several prescribed guidelines inform the agenda proposed to guide the present study:

1. Employ a rigorous, replicable, study design underpinned by validated theories of technology-user behaviour.
2. The study must be oriented towards the synergy between the technology, the mHealth tool, and end-user, the CHW.
3. Use a survey-based approach to collect data from a large sample of CHWs deployed within developing country mHealth projects in low-resource settings.
4. Similarly, collect data from a large supplementary sample of CHWs using traditional paper-based systems in low-resource developing country settings.
5. Use quantitative multi-factorial designs or multi-variate methods to systematically evaluate or empirically test mHealth impacts on CHW performance in the delivery of patient care.
6. Identify a set of CHW performance indicators with which to evaluate impacts using mHealth tools compared to traditional paper-based systems.
7. Explicate the causal mechanisms through which the technology (the mHealth tool) impacts user (CHW) performance.
8. Evaluate (i) the fit between CHW tasks and mHealth tools and (ii) impacts on mHealth tool use and CHW performance.
9. Evaluate (i) the use of mHealth tools by CHWs and (ii) determinants of mHealth tool use.

In congruence with the research questions and study objectives presented in Chapter 1, the shortcomings identified and discussed will be addressed in subsequent chapters of the present study. Consequently, the guidelines prescribed above must inform the trajectory of the study. In line with the above-stated guidelines, and in order to empirically demonstrate the importance of mHealth technology for CHW performance in low-resource settings in the context of the study, a quasi-experimental post-test was conducted, as detailed in Chapter 3.

3 The Impact of Mobile-Health (mHealth) Tools on the Performance of Community Health Workers (CHWs) in Kenya: A Quasi-Experiment

This chapter is an updated version of the publication: Gatara, M. and Cohen, J.F (2015) Mobile Health Tool Use and Community Health Worker Performance: A Quasi-Experimental Post-Test Perspective, *Journal for Health Informatics in Africa (JHIA)*, 2(2), pp. 44-54.

3.1 Introduction

In Chapter 2, mHealth tools were identified as having high potential to support CHWs at the point-of-care in low-resource settings (Liu et al., 2011; Perry and Zulliger, 2012). However, as described in Chapter 1, there is a lack of consensus on how to evaluate mHealth tool impacts. Moreover, there have been few studies conducted to examine the outcomes of mHealth tool use for CHW performance (Jaskiewicz and Tulenko, 2012). Therefore, to address the need for more robust evidence on the impacts of mHealth tools on CHWs (Bhutta et al., 2010), research questions 1 and 2 were formulated:

1. What are the differences in CHW performance using mHealth tools compared to those using traditional paper-based systems?
2. How are these differences indicative of expected positive mHealth tool impacts on CHW performance?

The purpose of this chapter is to address these two research questions. First, indicators with which to measure CHW performance are identified. Second, these indicators are used to compare the performance of a sample of CHWs using mHealth tools (the intervention group) against a sample using traditional, paper-based systems (the control or reference group). A quasi-experimental post-test only design was employed (Harris et al., 2006).

3.2 Conceptualizing Community Health Worker (CHW) Performance

To conceptualize and derive measures of CHW user performance, two areas of literature were reviewed. Given that CHWs are technology (mHealth tool) users, the general Information Systems (IS) literature was first reviewed to provide a basis for conceptualizing the broader concept of technology user performance. Second, the CHW mHealth literature was examined in order to derive a comparable set of performance indicators that reflect the specific context of CHW work, for purposes of this quasi-experimental study.

3.2.1 Perceived User Performance

In previous IS studies, user performance has been defined as the accomplishment of a set of tasks (Goodhue et al., 1997). The achievement of higher levels of user performance would require a combination of improved effectiveness, efficiency, and quality in the execution of technology-enabled work tasks (p. 452). First, *effectiveness* is the execution of actions or tasks to achieve desired work outcomes or results (Teo and Men, 2008). ITs have been shown to improve the effectiveness of users by enhancing their productive output in executing tasks (Torkzadeh and Doll, 1999). Second, *efficiency* is the completion of tasks in the least time, at the lowest cost (Garrity and Sanders, 1998). ITs have been shown to improve the efficiency of users by automating time-consuming tasks thereby reducing the wastage of resources (Belanger, Collins and Cheney, 2001). Third, *quality* is the completion of tasks without committing errors (Junglas et al., 2009). ITs have been shown to improve output quality not only by validating the inputs of users, but also minimizing errors in capturing and transmitting data (Belanger et al., 2001). In prior works, researchers have relied heavily on perceptual measures of the above dimensions of user performance (e.g. Henderson, 1988; Henderson and Lee, 1992; Teo and Men, 2008). Moreover, it has been found that these user performance measures are related to other outcomes such as enhanced decision-making speed (Leidner and Elam, 1993), improved user satisfaction (Seddon and Kiew; 1996), increased individual productivity (Igbaria and Tan, 1997), and maximized job performance (Becker, Billings, Eveleth and Gilbert, 1996).

In IS studies, perceptual measures of performance are preferred because indicators typically used tend to be intangible or qualitative, such that it becomes difficult to precisely quantify their actual value as objective quantifiable measurement criteria. Moreover, while objective indicators may be desirable, it is not always possible to compute exact measures of IT impacts (Henderson, 1988; Kemerer, 1989). Consequently, perceptual, self-reported, user-evaluated measures, have increasingly been adopted in IS research (Ives et al., 1983; DeLone and MacLean, 1992; Goodhue, 1992; Mahmood and Soon, 1991; Sethi and King, 1991). Thus performance can be a useful indicator of user perceptions of the importance or utility of ITs for their work tasks. Performance can also indicate a change in user perceptions of this importance or utility (Hou, 2012). The reliance of users on their perceptions in evaluating whether or not IT use for their tasks creates value, is based not only on personal experience or peer evaluations, but also on underlying expectations of performance. Consequently, the use of perceptual measures in IS research would constitute an acceptable approach to gauging user performance (Tallon, Kramer and Gurbaxani, 2000). From previous IS research, measures of user performance can thus be derived to reflect perceptual measures of (1) effectiveness, such as ‘the [system] increases my productivity’ (Torkzadeh and Doll, 1999), (2) efficiency, such as ‘the [system] helps me spend less time’ (Hou, 2012), and (3) quality, such as ‘the [system] decreases my error rates in reporting’ (Junglas et al., 2009). These measures of user performance employed in past studies are classified in the present study as Perceived User Performance (PUP) indicators. These indicators are summarized in Table 3.3.

3.2.2 Community Health Worker (CHW) Reporting Performance

In Chapter 2 it was established that self-reported measures of performance in CHW tasks such as reporting, have been used in few healthcare studies conducted in CHW mHealth settings. For example, self-reported measures have been used to indicate effectiveness e.g. ‘percentage of tasks completed during patient visits’ (Makoul, Raymond, Curry, Paul and Tang, 2001), efficiency e.g. ‘time spent capturing case records’ (Anantharaman and Han, 2001), and quality e.g. ‘errors observed for each task’ (Arango et al., 2011). In low-resource settings, CHWs are expected to transmit reports to hospitals and clinics on households visited and tasks completed (Braun et al., 2013). Reporting is thus an important part of how CHWs improve service delivery and link patients to the formal care system[17] (World Health Organization, 2006; Global Health Workforce, 2010). Consequently, performance in CHW work tasks such as reporting constitutes an important and useful dimension along which to evaluate the impacts of an IT-based intervention such as the use of an mHealth tool. Therefore, CHW performance in reporting is also operationalized in terms of self-reported dimensions of effectiveness, efficiency, and quality. These measures are classified in the present study as CHW Reporting Performance (CHWRP) indicators. These reporting indicators are summarized in Table 3.4. The quasi-experimental study conducted to compare CHW mHealth tool and traditional paper-based system users along both the PUP and CHWRP performance indicators, is described in Section 3.3.

3.3 Methods

A quasi-experimental post-test-only design with non-equivalent groups (Harris et al., 2006; Cook, Shadish and Wong, 2008; Leedy and Ormrod, 2013; Creswell, 2014) was used to achieve study objectives 1 and 2 of evaluating CHW performance using mHealth tools compared to traditional paper-based systems. For this type of design, there are two groups, one with an intervention (X) and the other without. The intervention (X) as implemented in one group can then be evaluated by comparing observed outcomes in the two groups. Since these groups are non-equivalent, confounding effects may be present (Harris et al., 2006). As a consequence, the effects of potential confounds on CHW performance must be tested for. This is to differentiate between effects on CHW performance that are due to the intervention (X) and those that are influenced by possible confounding variables. To enhance the likelihood of observing the true effect of the intervention (X), it is thus necessary to control for potential confounding variables (Harris et al., 2006, p. 18). In the present study, the intervention group, comprising CHWs using an mHealth tool, was compared to a reference (control) group, consisting of traditional paper-based system users. The intervention (X) is the use of an mHealth tool by CHWs. As such, CHW performance (O) in the mHealth tool (O1) and paper-based system (O2) user groups was examined. The relationship between these non-equivalent intervention and reference groups, is expressed as follows (Harris et al., 2006):

[17] Please refer Figure 2.2 in Chapter 2.

<u>Interventiongroup (mHealth Tool Users): X O1</u>

Controlgroup (Paper-Based System Users): O2

The use of a quasi-experimental design was motivated by two reasons. First, since the researcher did not introduce the intervention (refer section 2.8 for a discussion of the projects and Figure 2.7 for their geographic locations), random assignment of CHWs to the mHealth tool and paper-based system user groups was not possible. Second, it was not possible to establish baseline equivalence by conducting a pre-test since the intervention (mHealth tool use) was already underway (Leedy and Ormrod, 2013). Therefore, a post-test only design (Harris et al., 2006, p. 20) was the most feasible approach. For the purposes of data collection, administered self-reported structured questionnaires[18] were used to obtain 610 responses from CHWs. For the intervention group (X O1) comprising CHWs using mHealth tools, data were obtained from 257 respondents operating in sites in the peri-urban counties of Siaya, Nandi and Kilifi. For the reference group (O2) comprising CHWs using traditional paper-based systems, data were obtained from 353 respondents in the counties of Nairobi and Nakuru. To construct the sampling frame[19], a proportionate, stratified approach with systematic random sampling was used (Daniel, 2012). Specific Community Health Units (CHUs)[20] were identified within each of the counties. A proportional number of respondents were then systematically drawn from lists of CHWs operating in each CHU. Subsequent to collecting data using the structured questionnaires to elicit respondent data, the perceptual and self-reported performance of CHWs using mHealth tools could then be compared to those using traditional paper-based systems. The sample design used to elicit responses from these two groups of CHWs is depicted in Figure 3.1.

[18] The structured questionnaires used to collect data, are presented in Appendices P and Q.
[19] The sampling procedures used are discussed in Appendix A.
[20] A CHU is a community-based structure created by and within the Ministry of Health (MOH) through a link facility, and comprises CHWs supervised and led by a Community Health Extension Worker (CHEW) (Ministry of Public Health and Sanitation, 2013).

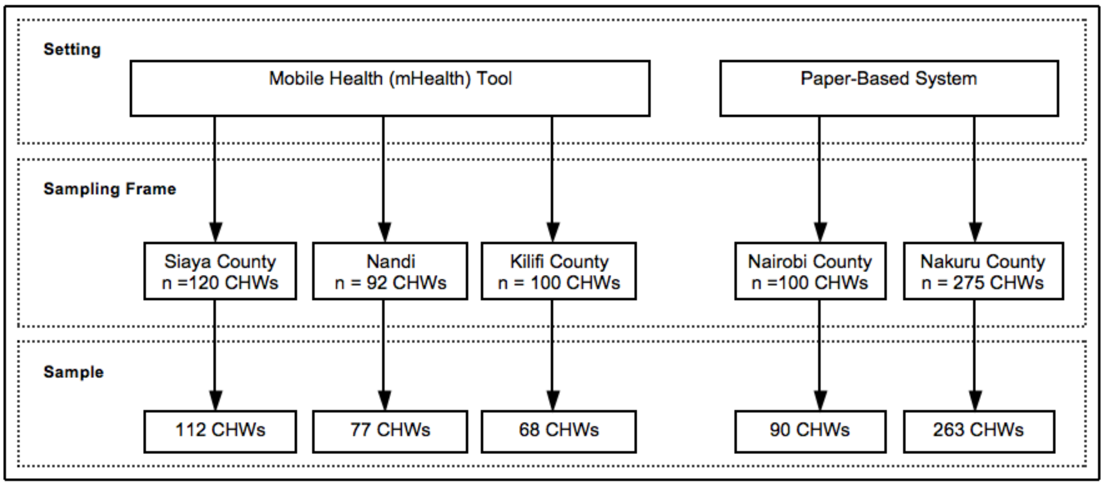

Figure 3.1. Sampling Frame

The counties identified are profiled in Table 3.1 (Kenya Population and Housing Census, 2009, p. 8).

Table 3.1. County Profiles

County	Region (Province)	Total Population	Land Area (km^2)	Density (Persons per km^2)
Siaya	Nyanza	743,946	2,530	333
Nandi	Rift Valley	842,304	3,029	261
Kilifi	Coast	1,109,735	12,609	12,607
Nairobi	Nairobi	3,138,369	695	4,515
Nakuru	Rift Valley	1,603,325	7,495	214

In the counties covered, CHWs are expected to support at least approximately 20 households[21] each, serving up to 100 patients (Ministry of Health, 2006). In each supported household, there are between 3 and 5 patients (Kenya Demographic and Health Survey, 2014). The Ministry of Health (MOH) in Kenya allocates the CHWs to Community Health Units (CHUs) from which the sampling[22] frame for the present study was derived. A proportionate number of CHWs from their respective CHUs were sampled. Irrespective of the intervention tool or system used, sampled CHWs were serving equivalent numbers of households in their respective counties. The intervention and control groups were therefore comparable as far as their average workloads (number of allocated households) were concerned. In addition to CHW coverage in the counties

[21] 43% of the household population is under the age of 15 years (Kenya Demographic and Health Survey Report, 2014).

[22] Details of the sampling criteria employed (including CHUs per county) are provided in Appendix A.

identified, the most recent MOH statistics (estimated in the year 2012) of reported rates[23] for all diseases (childhood morbidity), for children below 5 years of age, and the immunization rate (%) for children including (infants) aged between 12 and 23 months (Kenya Demographic and Health Survey, 2014; Kenya National Bureau of Statistics, 2014), are of significance to this study.

Table 3.2. Reported Health Rate Indicators and Outcomes		
County	Childhood (Morbidity) Reported Rate of Disease	Immunization Rate (%)
Siaya	97	72.5%
Nandi	91	64.2%
Kilifi	95	71.5%
Nairobi	71	60.4%
Nakuru	91	72.0%

Source: Kenya Demographic and Health Survey Report (2014); MOH (2015)

Table 3.2 indicates that the reported rates of all childhood diseases across the counties identified are within range. Moreover, the relative reported rate of immunization (%) for children below 5 years (and aged between 12 and 23 months) across the counties is similar. Furthermore, the distribution of reported childhood disease and immunization (%) is consistent. Notably, as there has been no significant variation across regions, the under-five mortality[24] index has been virtually the same in both rural and urban areas of Kenya (Kenya Demographic and Health Survey, 2014). In terms of child mortality, the challenges faced by patient populations across counties are therefore relatively similar. Thus as per reported childhood disease and immunization (%) rates and national under-five mortality estimates (Kenya Demographic and Health Survey, 2014; Ministry of Health (MOH) Estimates, 2015), population health outcomes in the counties identified are comparable. Thus, there are no notable or significant inhibiting regional or public health characteristics in the areas where CHWs are equipped with either an mHealth tool or

[23] County level data is limited as the Ministry of Health (MOH) only recently began aggregation of county-level indicators, particularly in those areas where mHealth projects were implemented (see Figure 2.7 in Chapter 2).

[24] In relation to child mortality and according to the Kenya Demographic and Health Survey Report (2014), the indicator of maternal mortality for the seven-year period from 2007 to 2014 averaged 362 deaths per 100,000 live births, with a range of between 254-471 (p. 8). Notably, the Millennium Development Goal (MDG) 4 set to attain the target of reducing the maternal mortality ratio by three quarters between 1990 and 2015, is yet to be attained (Millennium Development Goals (MDGs) Status Report for Kenya, 2012) thus CHWs remains a critical link to formal care in this respect (p. 17). The enhancement of CHW performance is therefore important for public health outcomes at the household level (State of Kenya Population 2010, 2011).

traditional paper-based system. Therefore households across the counties covered similarly require CHW intervention with a relative equivalence of trends in population health across the counties. Taken together, the average CHW workload and identified trends in population health across counties covered are indicative of a shared burden of task reporting at household level. Over time, equipping CHWs with mHealth tools may positively influence overall population health outcomes, but for now, the focus of this study is on the performance of the individual CHW user. Thus the intervention and control groups examined in this study are considered comparable.

The Perceived User Performance (PUP) indicators[25] comprised eight, seven-point Likert scale measurement items. Specifically, items 4, 5, 6, and 7 were adapted from Torkzadeh and Doll (1999) to measure the dimensions of user effectiveness, efficiency, and quality, as listed in Table 3.3. Items, 2, 3, and 8, were adapted from Junglas, Abraham and Ives (2009) to measure the dimensions of user effectiveness and quality. Item 1 was adapted from Hou (2012) to measure the dimension of effectiveness.

Table 3.3. Perceived User Performance (PUP) Indicators

Item	Indicator		Effectiveness	Efficiency	Quality
	Intervention Group	**Control (Reference) Group**			
1	The mHealth tool increases my productivity.	The paper-based system increases my productivity.	✓		
2	The mHealth tool increases my effectiveness with patients.	The paper-based system increases my effectiveness with patients.	✓		
3	The mHealth tool increases my quality of patient care.	The paper-based system increases my quality of patient care.			✓
4	The mHealth tool saves me time.	The paper-based system saves me time.		✓	
5	The mHealth tool enables me to complete tasks more quickly.	The paper-based system enables me to complete tasks more quickly.	✓		
6	Using the mHealth tool improves my effectiveness in completing tasks.	Using the paper-based system improves my effectiveness in completing tasks.	✓		
7	The mHealth tool improves the quality of my tasks.	The paper-based system improves the quality of my tasks.			✓
8	The mHealth tool decreases my reporting errors.	The paper-based system decreases my reporting errors.			✓

[25] The Perceived User Performance (PUP) construct is discussed in Appendix E3.

The contextualized, self-reported CHW Reporting Performance (CHWRP) measures comprised eleven indicators. First, workload (number of reported monthly cases) and throughput indicators (% of households visited monthly) were used to measure CHW effectiveness in reporting. Second, a flow time (hours spent completing case reports weekly) indicator was used to measure CHW efficiency in reporting. Third, error rate (% of reports returned to sender due to incorrect data) and completeness (% of complete monthly reports sent) indicators were used to measure CHW reporting quality. In addition to adapting items from the extant literature, the self-reported CHWRP indicators were informed by field discussions with health specialists and community coordinators. In addition, supplementary material provided by the Ministry of Health (MOH) such as CHW performance evaluation checklists, health extension worker indicators, and household registers were reviewed. The indicators used to measure self-reported CHW Reporting Performance (CHWRP) are classified in Table 3.4.

Table 3.4. Community Health Worker Reporting Performance (CHWRP) Indicators

Item	Statement	Dimension		
		Effectiveness	Efficiency	Quality
1	How many households do you visit per month?	✓		
2	What percentage of households visited are you able to report?	✓		
3	Of the households visited, how many monitoring cases do you report per month?	✓		
4	Of the households visited, how many prevention cases do you report per month?	✓		
5	Of the households visited, how many referral cases do you report per month?	✓		
6	In a typical week, how much time (in hours) do you take to complete monitoring case reports?		✓	
7	In a typical week, how much time (in hours) do you take to complete prevention case reports?		✓	
8	In a typical week, how much time (in hours) do you take to complete referral case reports?		✓	
9	Of the cases reported per month, approximately what percentage is completed on time?	✓		
10	Of the cases reported per month, what percentage is complete (no missing data)?			✓
11[26]	What percentage of completed reports is returned to you due to errors or inconsistencies?			✓

[26] This indicator was reverse-scored prior to analysis.

3.4 Results

3.4.1 Response Rate

The calculated response rates for the intervention and control groups are presented in Table 3.5.

Table 3.5. Response Rate

User Group	Invited Respondents	Actual Responses	Response Rate (%)	Number Missing Data	Number Usable Responses Retained
Mobile Health (mHealth) Tool (X O1)	312	257	82%	56	201
Paper-Based System (O2)	375	353	94%	136	217

Structured questionnaires were administered to 687 respondents, comprising 312 mHealth tool users from the intervention group (X O1) and 375 paper-based system users from the control group (O2). For the intervention group (X O1), 257 responses were obtained (82% response rate). First, 112 responses were obtained from the County of Siaya. Second, 77 responses were obtained from the County of Nandi. Third, 68 responses were obtained from the county of Kilifi. For the control group (O2), 353 responses were obtained (94% response rate). First, 90 responses were obtained from the County of Nairobi. Second, 263 responses were obtained from the County of Nakuru. The data obtained from respondents in the two user groups were screened[27] for missing values and outliers. Screening and missing value replacement resulted in 201 usable responses for the intervention group (X O1) of mHealth tool users, and 217 usable responses for the reference group (O2) of paper-based system users.

3.4.2 Demographics

The mHealth tool and paper-based system user groups were first compared along the demographic indicators of age, gender, education level, experience as a CHW, and use experience. CHW respondent ages in the mHealth tool and paper-based system user groups are shown in Table 3.6.

[27] A detailed description of data screening procedures is provided in Appendix D.

Table 3.6. Age				
	mHealth Tool User	% (100)	Paper-Based System User	% (100)
Age	**n = 201**		**n = 217**	
Below 25 Years	14	7.0	17	7.8
25-34 Years	102	50.7	79	36.4
35-44 Years	66	32.8	69	31.8
45-54	14	7.0	35	16.1
55-64 Years	3	1.5	14	6.5
65 Years and Above	1	0.5	1	0.5
Prefer Not to Say	0	0	1	0.5
Total	200	99.5	216	99.5
Missing	1	0.5	1	0.5
[a] Mann-Whitney U Test: U = 17885.500, p = **0.001**, two-tailed				

Table 3.6 indicates that most respondents across the two user groups were relatively young. Among mHealth tool users, respondents were mostly aged between 25 and 34 years (51%). The paper-based system users followed a similar trend (36%). However, a Mann-Whitney test conducted to compare these user groups (Brace et al., 2012) indicated a statistically significant difference in ages (U = 17885.500, $p < 0.05$). As shown in Figure 3.2, there were proportionately more paper-based system users aged 45 years or older.

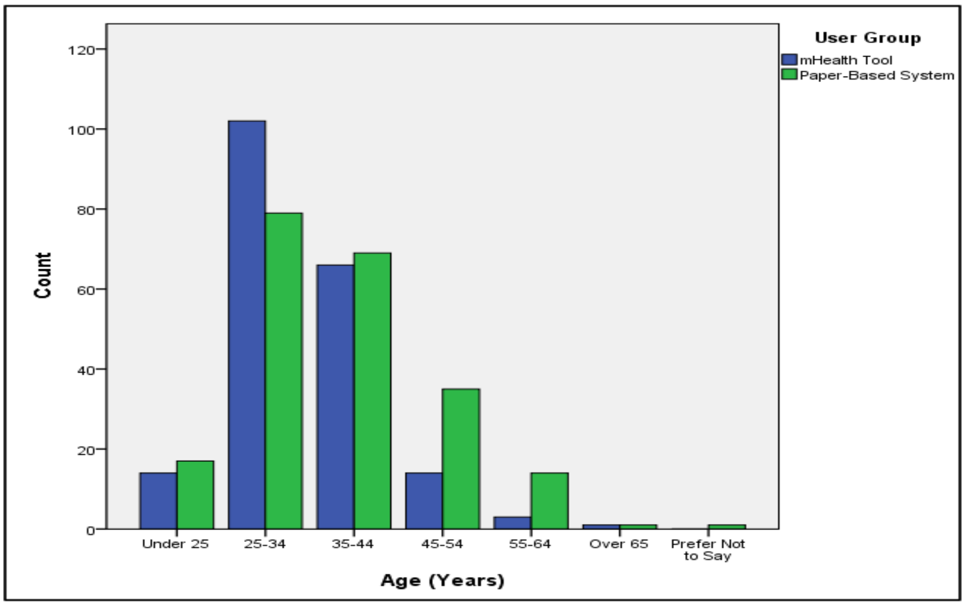

Figure 3.2. Age

The two user groups comprised more female than male CHW users. Specifically, 63% of mHealth tool users were females compared to 37% of males. Similarly, 65% of paper-based system users were females compared to 35% of males. Following a Chi-Square test

(Brace et al., 2012), no significant gender differences were found between the two user groups ($\chi^2 = 0.146$, $p = 0.703$).

Table 3.7. Gender				
	mHealth Tool User	% (100)	Paper-Based System User	% (100)
Gender	**n = 201**		**n = 217**	
Female	127	63.2	141	65.0
Male	74	36.8	76	35.0
Total	201	100	217	100
Missing	0	0	0	0
[b] Pearson Chi-Square Test: χ^2 (1, N = 418) = 0.146, p = 0.703				

The mHealth tool users mostly reported between 1 and 5 (57.2%), and 6 and 10 (30.3%) years of experience as CHWs. Similarly, the paper-based system users mostly reported between 1 and 5 (75.1%), and 6 and 10 (11.5%) years of experience as a CHW. The relative experience of CHWs using mHealth tool and paper-based systems is summarized in Table 3.8. Following a Kruskall-Wallis test (Brace et al., 2012) to compare the user groups, a statistically significant difference in CHW experience ($\chi^2 = 13.441$, $p = 0.000$) was observed.

Table 3.8. Experience as a CHW				
	mHealth Tool User	% (100)	Paper-Based System User	% (100)
Experience as a CHW	**n = 201**		**n = 217**	
Under 1 Year	14	7.0	17	7.8
1-5 Years	115	57.2	163	75.1
6-10 Years	61	30.3	25	11.5
Over 10 Years	5	2.5	7	3.2
Total	195	97.0	212	97.7
Missing	6	3.0	5	2.3
[c] Kruskal-Wallis Test: χ^2 (1, N = 418) = 13.441, p = 0.000				

The graph in Figure 3.3 shows that proportionately more paper-based system users reported up to 5 years of experience as a CHW. However, proportionately more mHealth tool users reported between 6 and 10 years of experience as a CHW. Of note, a comparison of medians in the two user groups (2 years for mHealth tool and paper-based system users) indicated that on average, CHWs reported equivalent levels of experience.

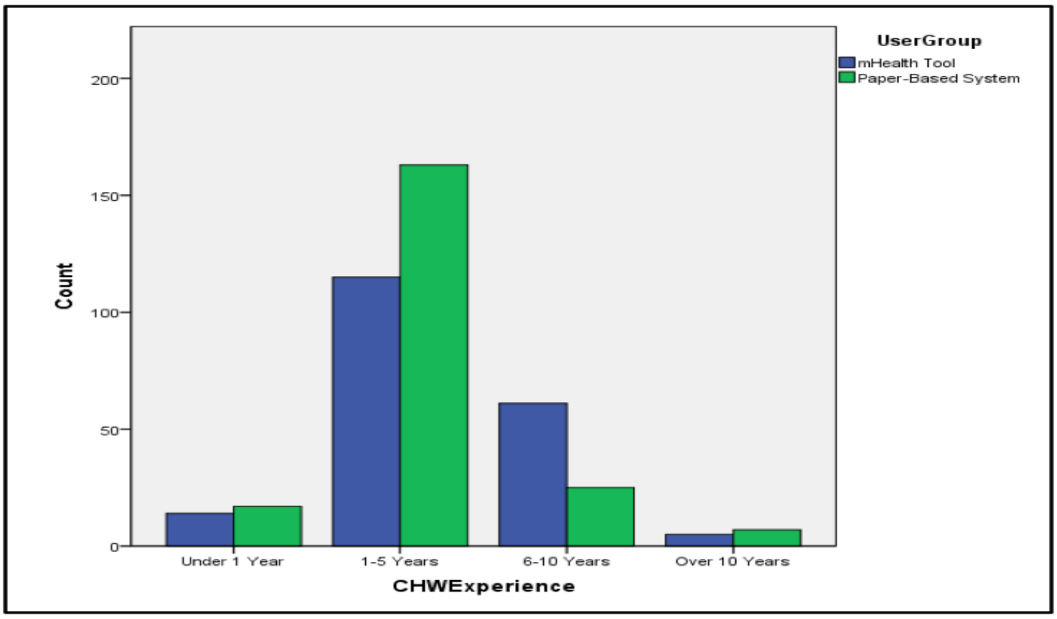

Figure 3.3. Experience as a CHW

The mHealth tool users were mostly educated up to secondary level (73.6%). Similarly, paper-based system users were mostly educated up to secondary level (73.6%). Education levels of mHealth tool and paper-based systems users are summarized in Table 3.9. Following a Kruskal-Wallis test (Brace et al., 2012) to compare the education levels of mHealth tool and paper-based system users, results indicated that there were no significant differences between the two user groups ($\chi^2 = 0.329$, $p = 0.566$).

Table 3.9. Education Level

	mHealth Tool User	% (100)	Paper-Based System User	% (100)
Education	**n = 201**		**n = 217**	
Secondary	148	73.6	166	76.5
Post-Secondary	35	17.4	34	15.7
Undergraduate	3	1.5	3	1.4
Postgraduate Diploma	7	3.5	8	3.7
Other	3	1.5	2	9
Total	196	97.5	213	98.2
Missing	5	2.5	4	1.8
[c] Kruskal-Wallis Test: χ^2 (1, N = 418) = 0.329, p = 0.566				

Similarly, there was no statistically significant difference ($\chi^2 = 0.019$, $p = 0.890$) in use experience between mHealth tool and paper-based system users. Table 3.10 indicates that most mHealth tool users mostly reported 5 or more months of use experience with the mHealth tool (79.1%). Similarly, most paper-based system users mostly reported 5 or more months of use experience with their paper-based tool (78.3%).

Table 3.10. Use Experience				
	mHealth Tool User	% (100)	Paper-Based System User	% (100)
Use Experience	**n = 201**		**n = 217**	
Less Than One Month	6	3.0	4	1.8
1-2 Month	1	0.5	14	6.5
3-4 Months	31	15.4	22	10.1
5 or More Months	159	79.1	170	78.3
Total	197	98.0	210	96.8
Missing	4	2.0	7	3.2
[d] Kruskal-Wallis Test: χ^2 (1, N = 418) = 0.019, p = 0.890				

Together, significant differences only in age and experience as a CHW were observed between the mHealth tool and paper-based system user groups. However, no significant gender, education level, and use experience differences between the two user groups were observed. Notably, a low number of respondents reported in the user experience categories of 'less than one month' and 'between 1 and 2 months'. Respondents falling into these very low experience categories were excluded from further analyses. Consequently, only responses from users reporting in the categories of 'between 3 and 4 months' and '5 or more months' of experience, were retained for analysis. This resulted in an mHealth tool user sample size of 190 and a paper-based user sample size of 192.

3.4.3 The Influence of User Group on Reporting Performance

The reporting performance of mHealth tool and paper-based system users was initially examined using Analysis of Covariance (ANCOVA) and compared along the eleven CHW Reporting Performance (CHWRP) indicators. The demographic variables of age and experience as a CHW were excluded from the ANCOVA due to their violation of statistical assumptions. For four CHWRP indicators (2, 5, 6, and 11), gender, education level, and use experience, were selectively controlled for, and in specific instances excluded due to their violation of these assumptions[28]. Since these assumptions were satisfied for the remaining seven CHWRP indicators (1, 3, 4, 7, 8, 9, and 10), gender, education level, and use experience, were included in the ANCOVA. However, as an

[28] Details of ANCOVA assumptions and criteria used to selectively control for gender, education level, and use experience, are provided in Appendix H.

additional check independent of ANCOVA assumptions, Hierarchical Regression [29] (Brace et al., 2012) was used to control for the potential confounding effects of age and experience as a CHW on each of the CHWRP indicators (1 to 11). In addition, gender, education level, and use experience, were included as control variables. Thus, Hierarchical Regression was used to control for all demographic variables. The ANCOVA and Hierarchical Regression results are summarized in Table 3.11. Results of the ANCOVA and Hierarchical Regression indicate that the two user groups differ significantly with respect to six of the eleven CHWRP indicators. These were indicator 5 (monthly referral cases reported), 6 (time spent completing monitoring case reports weekly), 7 (time spent completing prevention case reports weekly), 8 (time spent completing referral case reports weekly), 9 (percentage of reported monthly cases completed on time), and 10 (percentage of complete monthly cases reported). Independent T-Tests were conducted to observe user group differences in CHWRP indicators 5 to 8. The mHealth tool users reported higher numbers of hours spent on weekly monitoring, prevention, and referral case reports, with respect to CHWRP indicators 6, 7, and 8. These users reported higher percentages of monthly cases completed on time with respect to CHWRP indicator 9. There were also differences observed with respect to CHWRP indicators 6 to 8, where it appeared that the mHealth tool users save at least an hour, and up to two hours, in completing weekly case reports. However, with respect to CHWRP indicator 5, the mHealth tool users reported lower numbers of monthly referral cases.

[29] Using Hierarchical Regression, it was possible to control for the demographic variables of age and experience as a CHW, both previously excluded from ANCOVA. Moreover, Hierarchical Regression was used to ensure that potential confounding effects of all demographic variables on each of the CHWRP indicators (1 to 11) were controlled for. Details of Hierarchical Regression assumptions are provided in Appendix I.

Table 3.11. Analysis of Covariance (ANCOVA) and Hierarchical Regression Results								
Analysis of Covariance (ANCOVA) (a)					Hierarchical Regression (b)			
Item	**Indicator**	**F-ratio**	**Sig (p)**	**Partial η^2**	**Item**	**Indicator**	**Sig (p)**	**Beta (β)**
1	Monthly households visited[1a].	0.818	0.366	0.002	1	Monthly households visited[1b].	0.138	- 0.076
2	Percentage of monthly household visits reported.	1.867	0.173	0.005	2	Percentage of monthly household visits reported[2b].	0.065	- 0.094
3	Monthly monitoring cases reported.	0.044	0.833	0.000	3	Monthly monitoring cases reported[3b].	0.857	- 0.012
4	Monthly prevention cases reported.	0.030	0.862	0.000	4	Monthly prevention cases reported[4b].	0.820	0.015
5	Monthly referral cases reported.	5.182	0.024*	0.026	5	Monthly referral cases reported.	0.016*	0.175
6	Time spent completing monitoring case reports weekly[2a].	13.704	0.000***	0.043	6	Time spent completing monitoring case reports weekly[5b].	0.000***	0.206
7	Time spent completing prevention case reports weekly.	4.360	0.038*	0.014	7	Time spent completing prevention case reports weekly.	0.025*	0.130
8	Time spent completing referral case reports weekly.	23.502	0.000***	0.074	8	Time spent completing referral case reports weekly.	0.000***	0.267
9	Percentage of reported monthly cases completed on time[3a].	26.640	0.000***	0.082	9	Percentage of reported monthly cases completed on time[6b].	0.000***	- 0.229
10	Percentage of complete monthly cases reported[4a].	17.622	0.000***	0.043	10	Percentage of complete monthly cases reported[7b].	0.000***	- 0.181
11	Percentage of reports completed without errors.	0.069	0.793	0.000	11	Percentage of reports completed without errors.	0.978	- 0.002

******* $p < 0.0001$, ****** $p < 0.01$, ***** $p < 0.05$

1a Use experience (F (1, 384) = 4.172, p = 0.013*, partial η^2 = 0.016) and education level (F (1, 384) = 10.475, p = 0.001**, partial η^2 = 0.027) were found to have effects on CHWRP 1. **2a** Gender (F (1, 306) = 4.432, p = 0.036, partial η^2 = 0.014) was found to have an effect on CHWRP 6. **3a** Use experience (F (1, 300) = 4.219, p = 0.041, partial η^2 = 0.014) was found to have an effect on CHWRP 9. **4a** Use experience (F (1, 393) = 18.562, p = 0.000, partial η^2 = 0.045) was found to have an effect on CHWRP 10. **1b** *Age* (p = 0.017*, beta (β) = 0.124) and education level (p = 0.003* and beta (β) = -0.147) were found to have an effect on CHWRP 1. **2b** *Use experience* (p = 0.000***, beta (β) = 0.249) was found to have an effect on CHWRP 2. **3b** *Experience as a CHW* (p = 0.042*, beta (β) = 0.137) was found to have an effect on CHWRP 3. **4b** *Experience as a CHW* (p = 0.001***, beta (β) = 0.233) was found to have an effect on CHWRP 4. **5b** *Gender* (p = 0.022*, beta (β) = - 0.0127) was found to have an effect on CHWRP 6. **6b** *Use experience* (p = 0.000***, beta (β) = 0.229) was found to have an effect on CHWRP 9. **7b** *Use experience* (p = 0.000***, beta (β) = 0.210) was found to have an effect on CHWRP 10.

First, the difference between user groups with respect to CHWRP 5 (*monthly referral cases reported*) was statistically significant (t = -2.183, df = 255.000, p = 0.15, one-tailed). Contrary to expectations, mHealth tool users (mean = 5.5 hours) report fewer monthly referral cases than paper-based system users (mean = 6.5 hours). Error bars indicating sample means (with 95% confidence intervals) for both user groups with respect to CHWRP5 are shown in Figure 3.4. It appears that the CHWs using a traditional paper-based system to report referred cases on a monthly basis are outperforming their counterparts using an mHealth tool. The paper-based system using CHWs may be either be more experienced or more comfortable at using conventional means to refer patients, such that using an mHealth tool is not preferable. This unexpected finding may be an indicator that reporting on referral cases may be less cumbersome using paper-based systems, to which users are accustomed.

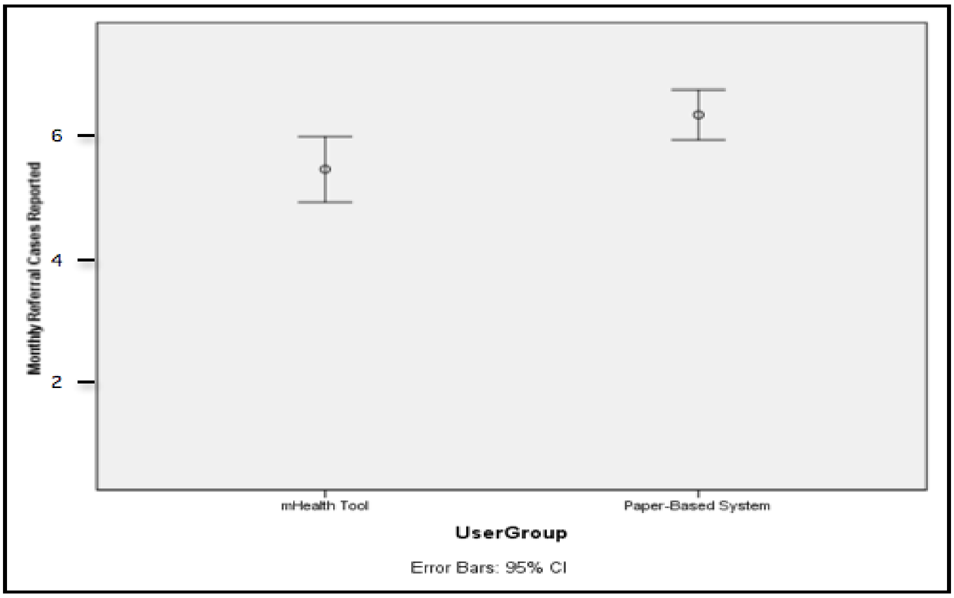

Figure 3.4.Error Bars: Monthly Referral Cases Reported

To further ascertain this difference in reported referrals, the interaction effects between experience as a CHW and user group on CHWRP 5 were plotted, as shown in Figure 3.5.

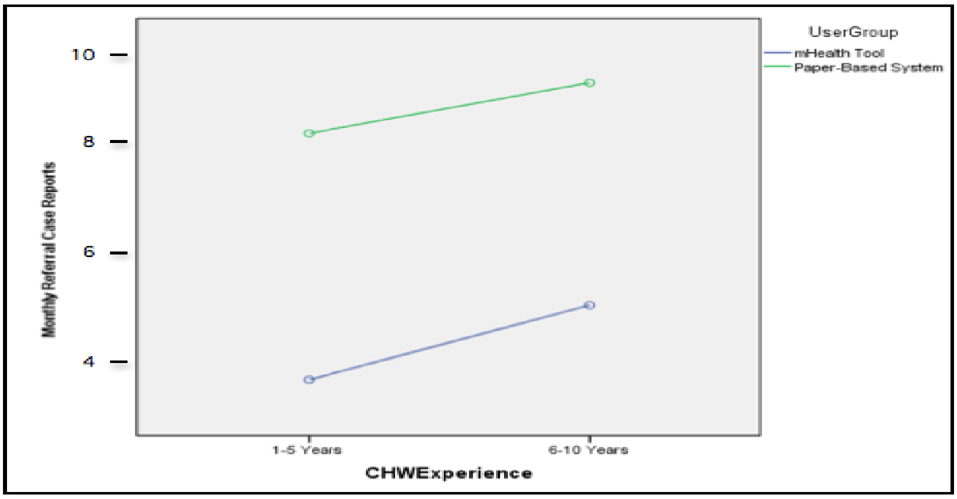

Figure 3.5. Effect of Experience as a CHW on Monthly Referral Cases Reported

Figure 3.5 indicates that at all levels of experience as a CHW, paper-based system users appear to be a significantly higher number of monthly referrals than mHealth tool users. This result further indicates that perhaps users may be encountering functional difficulties referring patients using the mHealth tool. In this regard, the mHealth tool interface may not be designed to optimize reporting task performance on referral cases, and as a result is not functioning as well. Nevertheless, further analysis on reporting performance in referral is warranted.

Second, the difference between mHealth tool and paper-based system users with respect to CHWRP 6 (*time spent completing monitoring case reports weekly*) was statistically significant (t = -3.565, df = 253.592, p = 0.000, one-tailed). CHWs using mHealth tools (mean = 3 hours) reported less time completing weekly monitoring case reports than paper-based system users (mean = 4 hours). Error bars indicating the sample means (with 95% confidence intervals) for both user groups with respect to CHWRP 6 are shown in Figure 3.6.

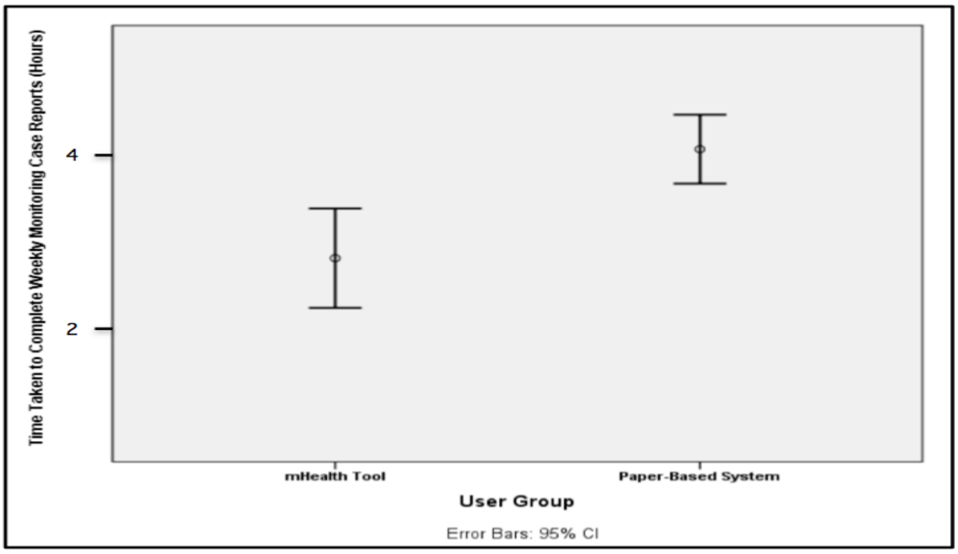

Figure 3.6. Error Bars: Mean Time Taken to Complete Weekly Monitoring Case Reports (Hours)

Third, the difference between user groups with respect to CHWRP 7 (*time spent completing prevention case reports weekly*) was statistically significant (t = -1.727, df = 246.136, p = 0.0425, one-tailed). Compared to paper-based system users, mHealth tool users (mean = 3 hours) reported less time spent completing weekly prevention case reports than their counterparts (mean = 4 hours). Error bars indicating the sample means (with 95% confidence intervals) for both user groups with respect to CHWRP 7 are shown in Figure 3.7 (a). Fourth, the difference between user groups with respect to OUP 8 (*time spent completing referral case reports weekly*) was statistically significant (t = -4.892, df = 310.000, p = 0.000, one-tailed). Compared to CHWs using paper-based systems, mHealth tool users (mean = 1 hour) reported less time spent completing weekly referral cases (mean = 3 hours). Error bars, indicating the sample means (with 95% confidence intervals) for both user groups with respect to CHWRP 8, are shown in Figure 3.7 (b).

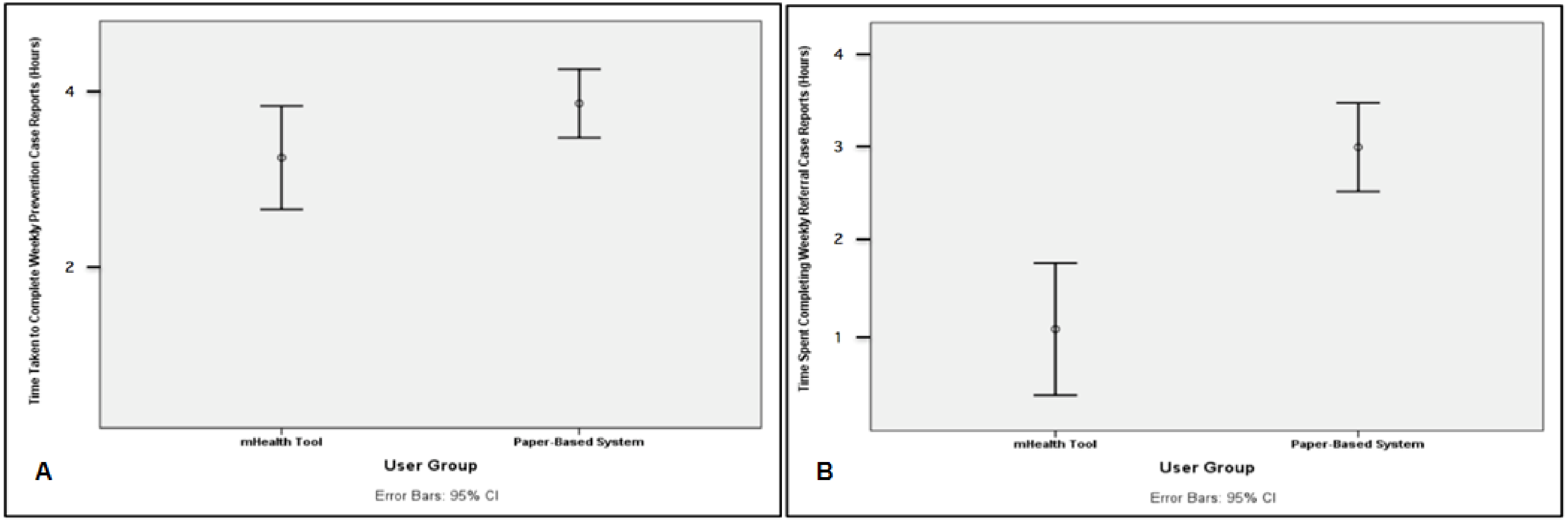

Figure 3.7. Error Bars: Weekly Case Reports for (a) Prevention (b) Referral

The percentages of monthly reported cases completed on time (CHWRP 9) in the mHealth tool and paper-based system user groups are shown in Figure 3.8. The graph in Figure 3.8 shows that while 30% of CHWs using mHealth tools reported over 90-100% of cases on time, only 10% of their counterparts using paper-based systems accomplished the same quantity. Moreover, 65% of CHWs using mHealth tools reported more than 60% of cases on time, compared to 46% using paper-based systems.

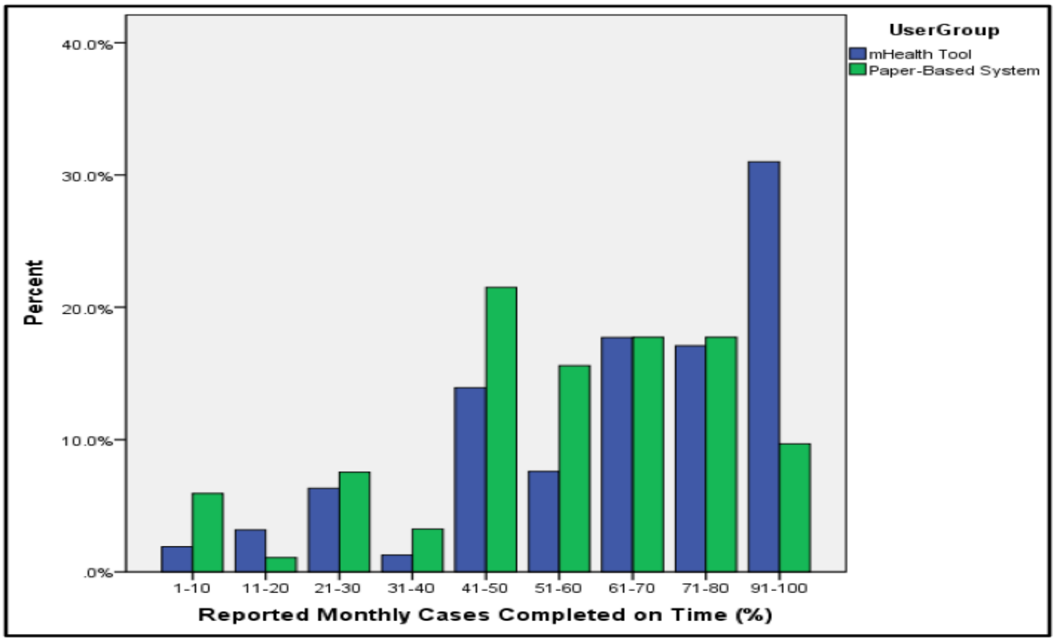

Figure 3.8. Group Differences in Monthly Cases Completed on Time

The differences in percentage of complete monthly case reports (CHWRP 11) as reported by mHealth tool and paper-based system users are shown in Figure 3.9. Compared to paper-based system users, CHWs who use mHealth tools reported higher percentages of complete monthly cases (no missing data entries). Moreover, 37% of mHealth tool users reported over 90% of complete cases, compared to 17% using paper-based systems.

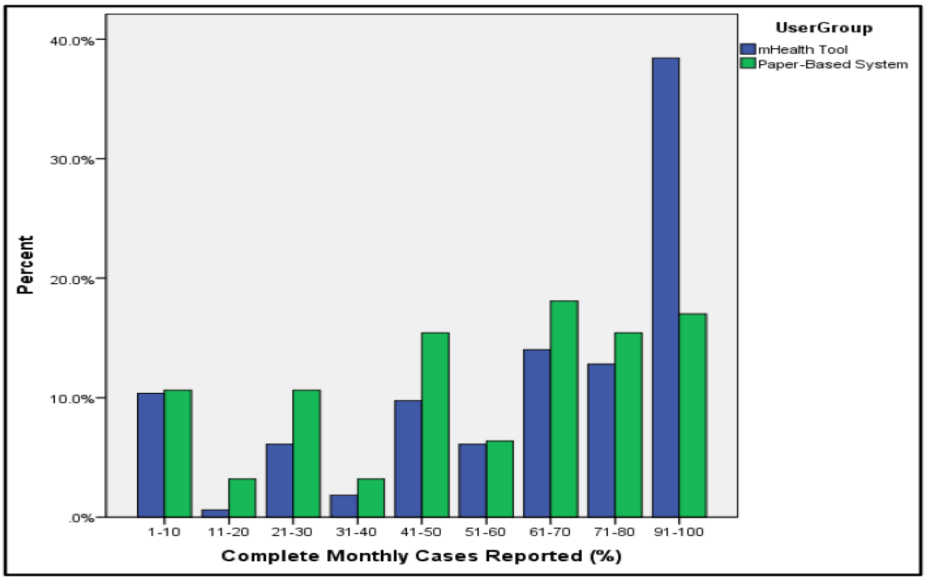

Figure 3.9. Clustered Bar Chart: Group Differences in Complete Monthly Cases

The ANCOVA results show that the demographic indicators of use experience and gender had significant confounding effects on the three CHWRP indicators 1 (monthly households visited), 6 (time spent completing monitoring case reports weekly), and 10 (percentage of complete monthly cases reported). The Hierarchical Regression results show that the demographic indicators of age, education level, use experience, experience as a CHW, and gender, had significant confounding effects on seven CHWRP indicators including 1 (monthly households visited), 2 (percentage of monthly household visits reported), 3 (monthly monitoring cases reported), 4 (monthly prevention cases reported), 6 (time spent completing monitoring case reports weekly), 9 (percentage of reported monthly cases completed on time), and 10 (percentage of complete monthly cases reported). These effects are further described below.

The demographic indicator of age (p = 0.017, beta (β) = 0.124) was found to have a significant effect on CHWRP 1 (households visited monthly). The interaction effect between age and user group on CHWRP 1 (households visited monthly) is shown in Figure 3.10. CHWs aged below 25 years, using paper-based systems, reported a slightly higher number of monthly household visits than mHealth tool users. In the two user groups, CHWs aged between 25 and 34 years reported equivalent households monthly visitations. However, among CHWs aged 25 years and older, mHealth tool users reported a significantly higher number of household visits compared to their paper-based system using counterparts.

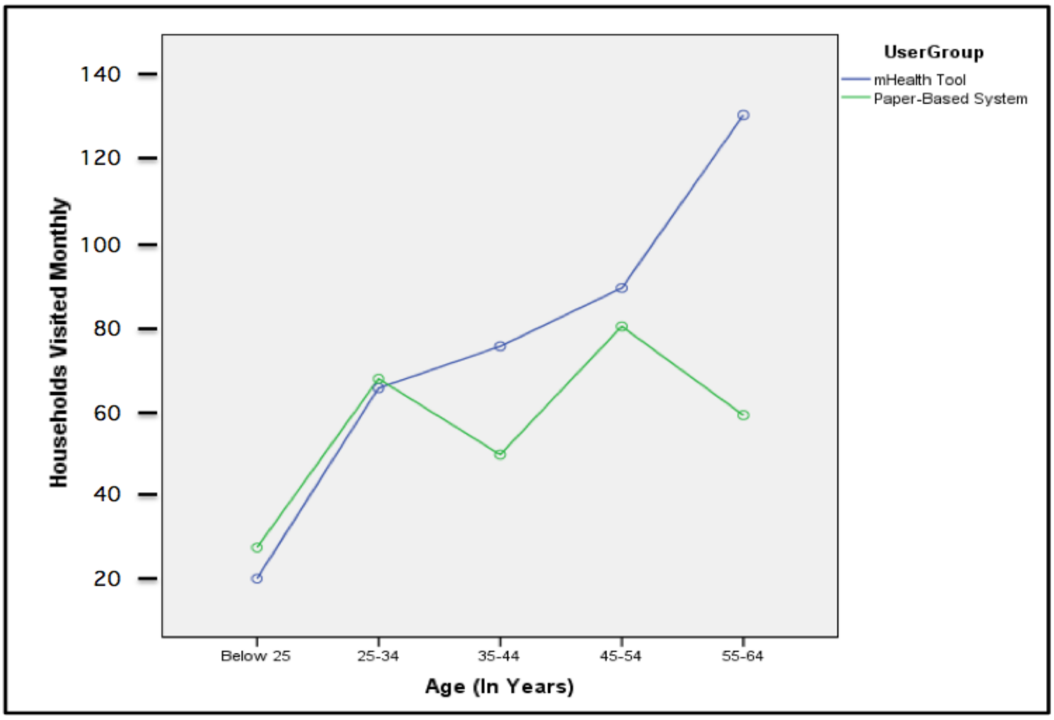

Figure 3.10. Effect of Age on Households Visited Monthly

The graph in Figure 3.11 indicates that the youngest mHealth tool users reported a lower number of monthly household visits. Thus the mHealth tool appears to strengthen the performance of older CHWs as among these respondents, a steady increase in reporting was experienced. It was also found that *use experience* has a significant effect ($F(1, 384) = 4.172$, $p = 0.013$, partial $\eta^2 = 0.016$) on CHWRP 1 (*households visited monthly*). The interaction effects of *use experience* and *user group* on indicator CHWRP 1 is shown in Figure 3.11.

The graph in Figure 3.11 shows that in the initial months of use, CHWs using mHealth tools reported fewer monthly households visited than paper-based system users. However, after five or more months of use, mHealth tool users reported higher numbers of monthly household visits. The mHealth tool users appear to be slower at first (possibly due to a technology learning curve) but after gaining enough experience they eventually report a higher number of monthly household visits. Experience with the paper-tool does not appear to have a similar effect on user performance as the line is flat.

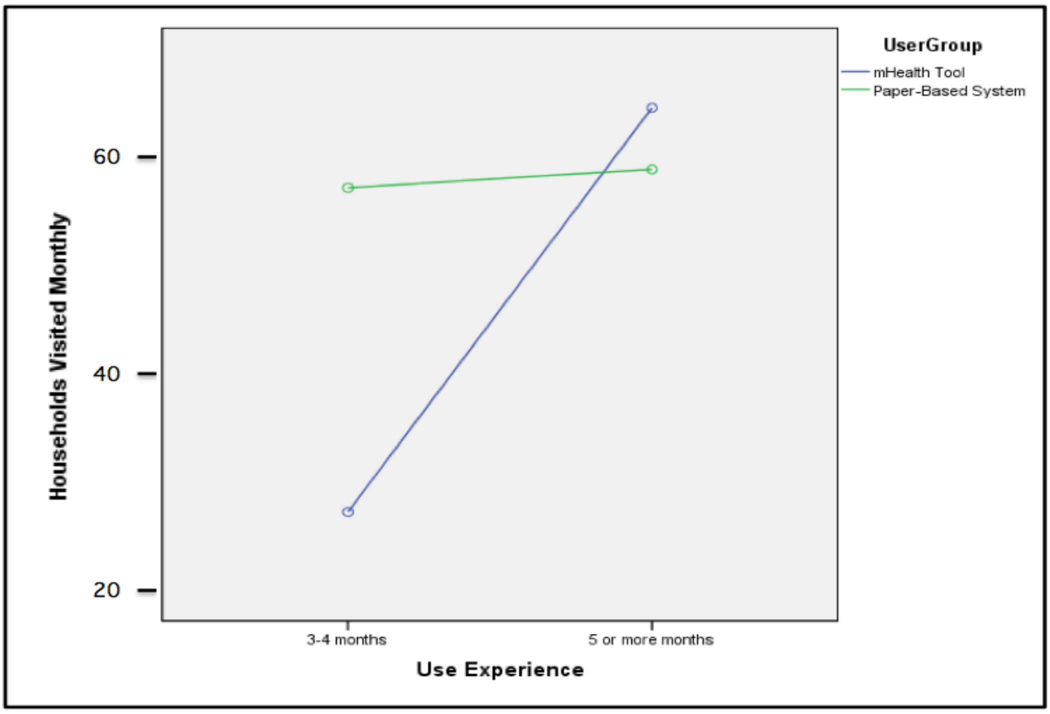

Figure 3.11. Effect of Use Experience on Households Visited Monthly

Following ANCOVA (F (1, 384) = 10.475, p = 0.001, partial η^2 = 0.027) and Hierarchical Regression (p = 0.003* and beta (β) = -0.147), *education level* was found to have a significant effect on CHWRP 1 (*households visited monthly*). The effect of the interaction between *education level* and *user group* on indicator CHWRP 1 is shown in Figure 3.12. Compared to paper-based system users, mHealth tool users reported a higher number of households visited monthly. However, at the post-secondary education level, paper-based system users reported a higher number of monthly household visits. The reported monthly household visits appear to decrease as education levels increase, especially among mHealth tool users. The decline in monthly visits reported could be attributed to more educated CHWs reporting fewer but more complex cases based on their availability, due to other engagements. Nonetheless, this declining trend warrants further investigation.

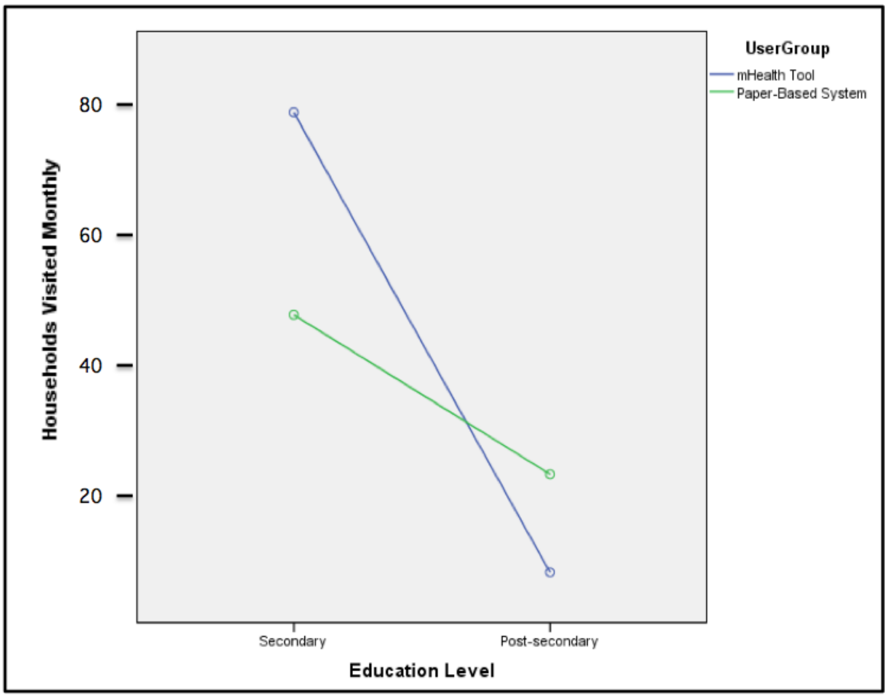

Figure 3.12. Effect of Education Level on Households Visited Monthly

Use experience was also found to have an effect (p = 0.000, beta (β) = 0.249) on CHWRP 2 (*percentage of monthly household visits reported*). The interaction effect of *use experience* and *user group* on CHWRP 2 is shown in Figure 3.13. Compared to paper-based system users, as CHWs using mHealth tools gain use experience, they tend to report higher percentages of households visited monthly. Notably, mHealth tool users seem to struggle initially, gradually improving with experience to eventually overtake their paper-based system using counterparts after five or more months of use.

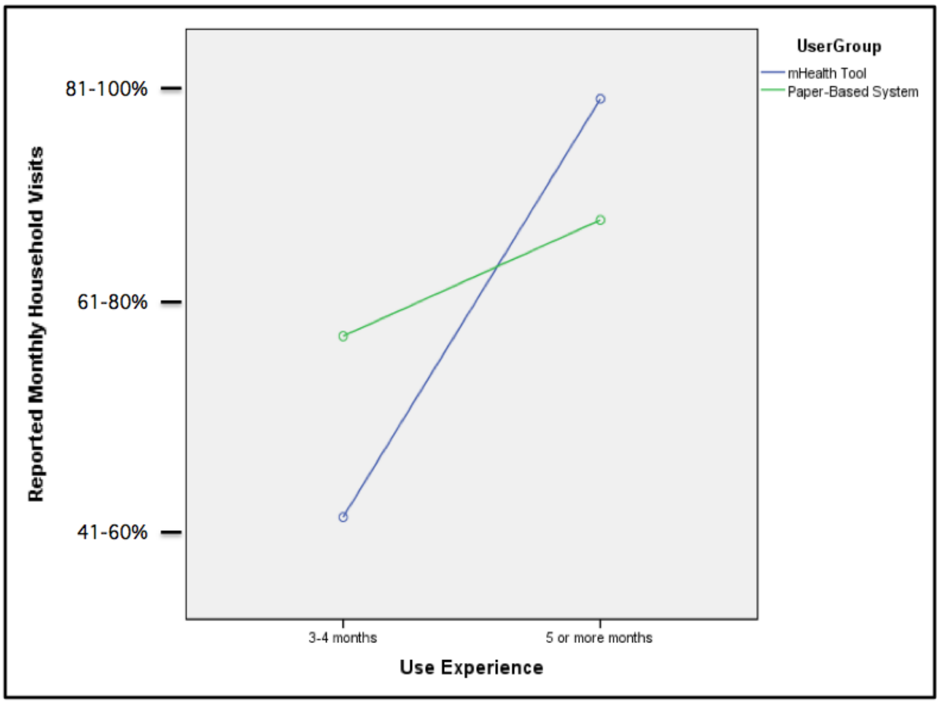

Figure 3.13. Effect of Use Experience on Households Visited Monthly

Experience as a CHW was found to have an effect (p = 0.042, beta (β) = 0.137) on CHWRP 3 (*monthly monitoring cases reported*). The effects of the interaction between *experience as a CHW* and *user group* on CHWRP 3 is shown in Figure 3.14 (a). Compared to paper-based system users, mHealth tool users with less than 1 year of experience as a CHW reported a higher number of monthly monitoring cases. However, between 6 and 10 years of experience as a CHW, paper-based system users reported a marginally higher number of monthly monitoring cases than their counterparts. Of note, both mHealth tool and paper-based system users with between 1 and 5 years of experience as a CHW reported an equivalent number of monitoring cases monthly. Moreover, mHealth tool users appear to report as many, or more, monthly monitoring cases than their paper-based system using counterparts at all levels of CHW experience, except between 6 and 10 years where there are marginally fewer. The most experienced CHWs using mHealth tools reported significantly higher numbers than paper-based system users. A similar pattern is evident for prevention cases reported (Figure 3.14 (b)).

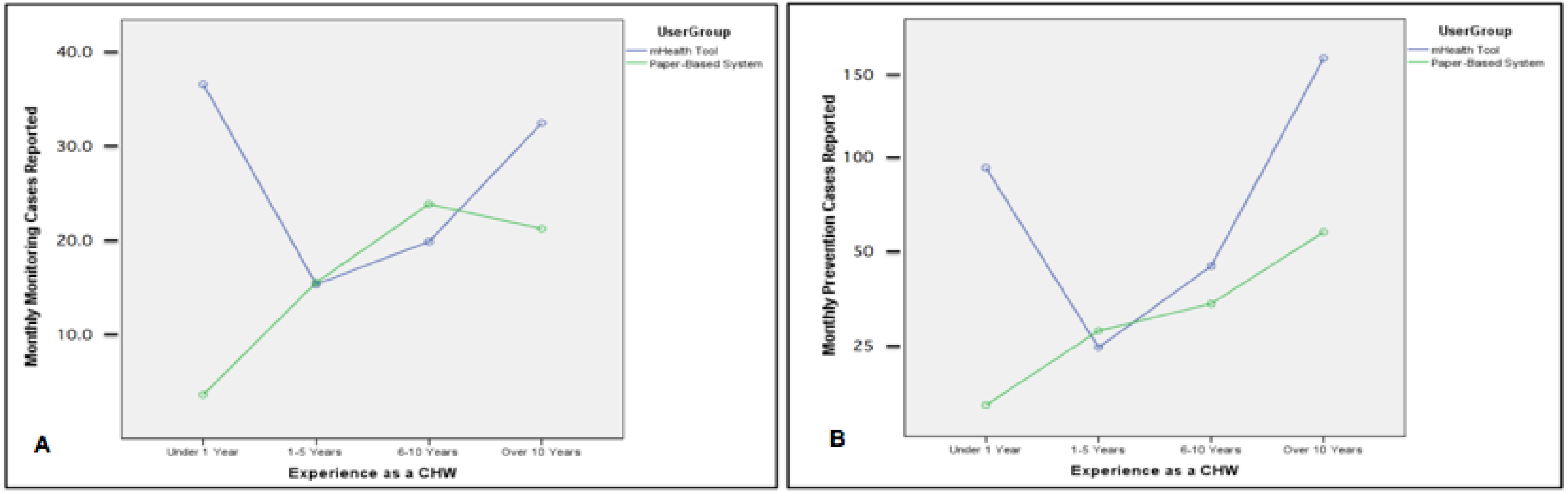

Figure 3.14.. Effect of Experience on Reported Monthly Cases of (a) Monitoring (b) Prevention

Gender was found to have an effect (p = 0.022, beta (β) = - 0.0127) on CHWRP 6 (*time spent completing monitoring case reports* weekly). The effects of the interaction between *gender* and *user group* on CHWRP 6 is shown in Figure 3.15. Compared to paper-based system users, mHealth tool users reported completion of weekly monitoring case reports in significantly fewer hours. In both groups, female CHWs reported less time spent reporting weekly monitoring cases than their male counterparts. However, both genders seem to perform well with the mHealth tool.

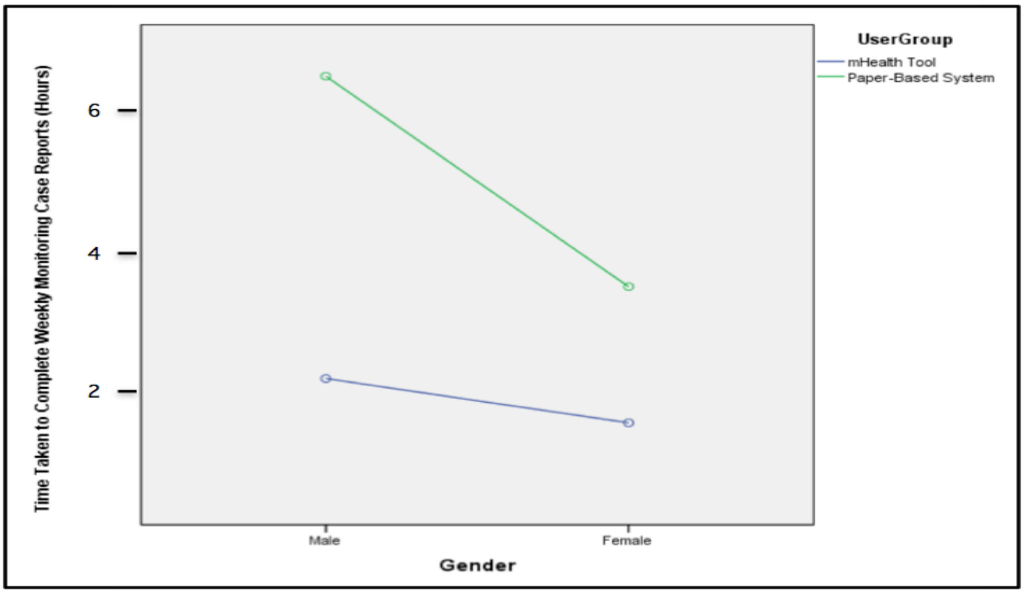

Figure 3.15. Effect of Gender on Monitoring Case Reports Completed Weekly

Following ANCOVA (*F* (1, 300) = 4.219, p = 0.041, partial η^2 = 0.014) and Hierarchical Regression (p = 0.000, beta (β) = 0.229), *use experience* was found to have an effect on CHWRP 10 (*percentage of reported monthly cases completed on time).* The interaction between *use experience* and *user group* along CHWRP 10 is shown in Figure 3.16.

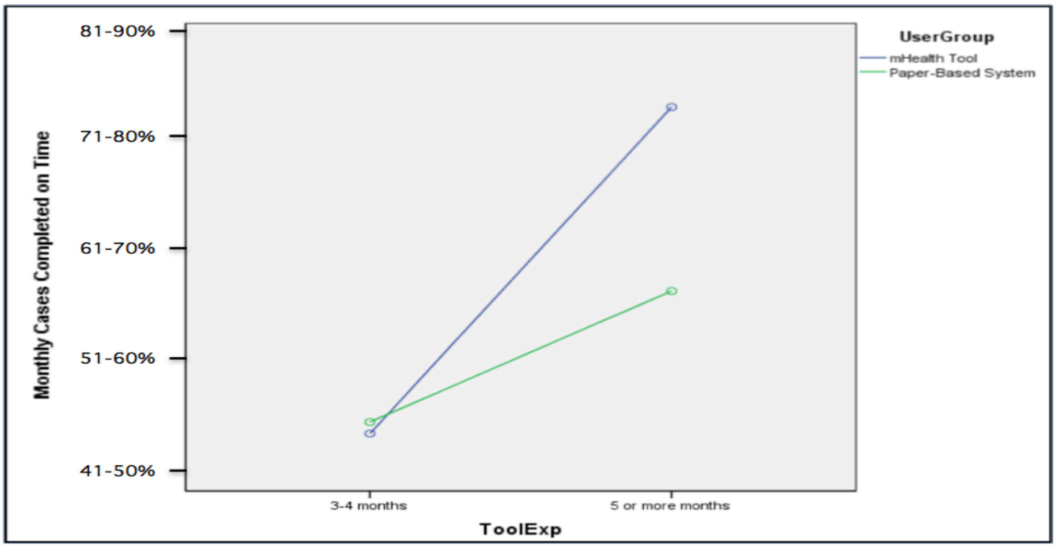

Figure 3.16. Effect of User Experience on Monthly Cases Reported on Time

The graph in Figure 3.16 indicates that in the early months of use, CHWs using mHealth tools reported marginally fewer monthly cases completed on time than paper-based system users. However, after five or more months of use, mHealth tool users report significantly higher percentages. The mHealth tool users may appear to be slower at first, but gradually accumulate sufficient experience to report higher percentages of monthly cases completed on time.

Following ANCOVA (F (1, 393) = 18.562, p = 0.000, partial η^2 = 0.045) and Hierarchical Regression (p = 0.000, beta (β) = 0.210), *use experience* was found to have an effect on CHWRP 11 (*percentage of complete monthly cases reported*). The interaction between *use experience* and *user group* along CHWRP 11 is shown in Figure 3.17. Compared to paper-based system users, CHWs using mHealth tools reported higher percentages of complete monthly case reports (no missing data entries).

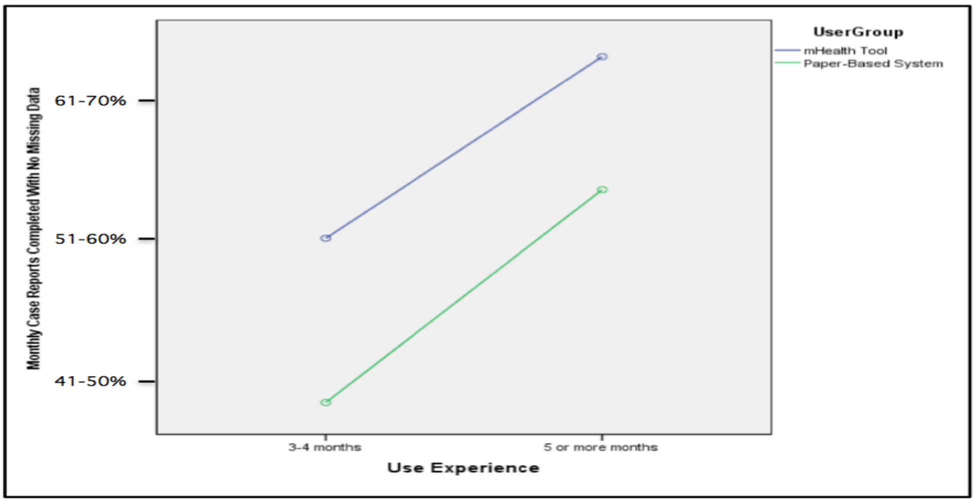

Figure 3.17. Effect of User Experience on ‘Complete’ Monthly Cases Reported

Significant results following of the quasi-experimental study are summarized in Table 3.12.

Table 3.12. Significant Findings of Quasi-Experimental Study								
Community Health Worker Reporting Performance		**Main Effect (Group)**		**Interaction Effect (Confound)**				
Item	Indicator	Yes	No	Age	Gender	Education Level	Experience as a CHW	Use Experience
1	Monthly households visited[1].		✓	✓		✓		✓
2	Percentage of monthly household visits reported[1].		✓					✓
3	Monthly monitoring cases reported[1].		✓				✓	
4	Monthly prevention cases reported[1].		✓				✓	
5	Monthly referral cases reported[1].	✓						
6	Time spent completing monitoring case reports weekly[2].	✓			✓			
7	Time spent completing prevention case reports weekly[2].	✓						
8	Time spent completing referral case reports weekly[2].	✓						
9	Percentage of reported monthly cases completed on time[1].	✓						✓
10	Percentage of complete monthly cases reported[3].	✓						✓
11	Percentage of reports completed without errors or inconsistencies[3].		✓					

User Performance Dimensions: **1** = Effectiveness **2** = Efficiency **3** = Quality

Table 3.12 indicates that a number of group performance and confounding effects were observed. First, mHealth tool users reported less time spent completing monitoring, prevention, and referral cases weekly, and higher levels of monthly cases completed on time. They also reported a higher volume of reports completed without errors. Second, mHealth tool users report higher levels of monthly household visits depending on age, education level, and use experience. These users report higher levels of monitoring and prevention cases monthly depending on experience as a CHW, and monitoring cases weekly depending on gender. They also report higher levels of monthly cases completed on time and higher volumes completed without errors, depending on use experience.

3.4.4 The Influence of User Group on Perceived User Performance

User performance using mHealth tools and paper-based systems was descriptively compared along the eight perceptual indicators (PUP 1 – 8)[30] introduced in Table 3.1. The means and confidence intervals for the two groups are depicted as error bars in Figure 3.18. CHWs using mHealth tools had generally higher perceptions of performance impacts than paper-based system users along all of the indicators.

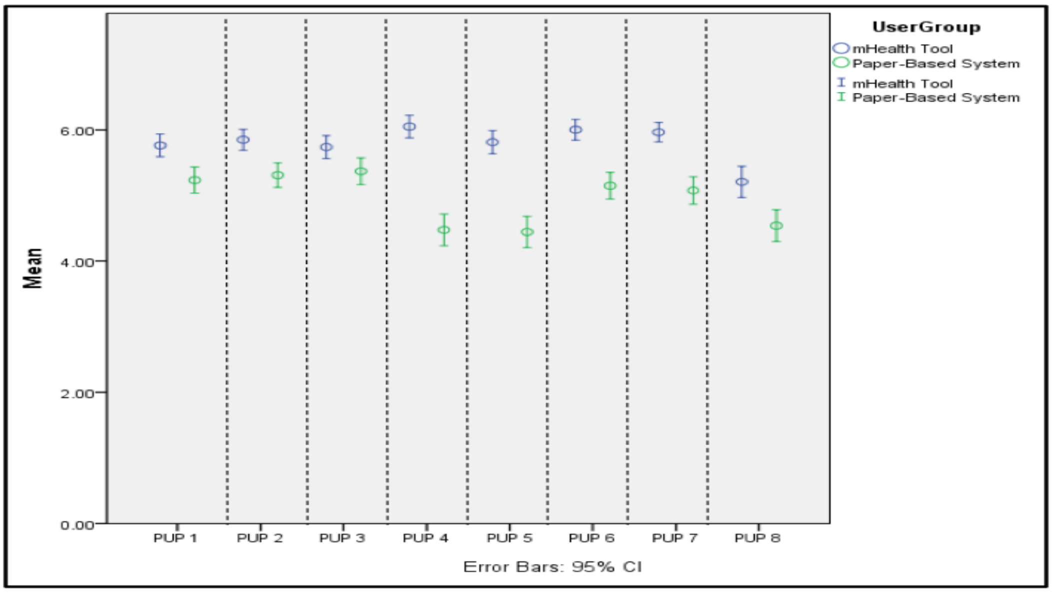

Figure 3.18. Perceptual User Performance (PUP) Means: 95% Confidence Intervals

[30] **PUP 1** The mHealth tool / paper-based system increases my productivity, **PUP 2** The mHealth tool / paper-based system increases my effectiveness with patients, **PUP 3** The mHealth tool / paper-based system increases my quality of patient care, **PUP 4** The mHealth tool / paper-based system saves me time, **PUP 5** The mHealth tool / paper-based system enables me to complete tasks more quickly, **PUP 6** Using the mHealth tool / paper-based system improves my effectiveness in completing tasks, **PUP 7** The mHealth tool / paper-based system improves the quality of my tasks, **PUP 8** The mHealth tool / paper-based system decreases my reporting errors.

3.5 Chapter Conclusion

The purpose of this chapter was to add to the evidence on the impacts of mHealth by comparing performance of CHWs using the mHealth tool compared to those using traditional paper-based systems. A quasi-experimental post-test-only design with non-equivalent groups (Harris et al., 2006) was used to compare the CHWs using mHealth tools with those using paper-based systems along two sets of indicators. First, typical self-reported indicators of CHW task reporting performance were used. Second, perceptual indicators of tool or system impacts on the effectiveness, efficiency and quality, of individual tasks were examined.

In summary, findings indicated that mHealth tool users outperform paper-based system users by spending less time to complete monitoring, prevention, and referral reports weekly, and reporting higher percentages of both timeous and complete monthly cases. In general, the older mHealth tool users outperform their younger counterparts in reporting a higher number of monthly household visits. In the initial months of use, less experienced mHealth tool users appear to outperform paper-based system users in reporting monthly household visits. However, after a period of at least five months, it appears that mHealth tool users have accumulated sufficient experience to outperform their counterparts. The mHealth tool users tend to report higher percentages of monthly household visits than paper-based system users as they gain in experience. A similar trend in monthly reported cases completed on time was also evident. At every level of use experience, mHealth tool users appear to outperform paper-bases system users at reporting complete monthly cases. It also appears that they report equivalent or higher numbers of monthly monitoring cases than paper-based system users, but less so with between six and ten years of experience as CHWs. In general, the most experienced users report higher numbers using an mHealth tool. A similar trend in reporting of monthly prevention cases was observed. The mHealth tool and paper-based system using females appear to outperform their male counterparts by spending less time to complete weekly monitoring case reports. The findings that mHealth tool users report fewer monthly referral cases than paper-based system users, and appeared to report fewer monthly household visits as education levels increase, were unanticipated and require further investigation in future work. Lastly, mHealth tool users were found to be more positive about the effects of their tool on their performance, than those using paper-based systems, particularly with regards to its time-saving.

4 The Theoretical Underpinnings of the Technology-to-Performance Chain (TPC)

4.1 Introduction

Having now established that on average mHealth tools influence superior user performance over traditional paper-based systems, the subsequent step in the present study is to examine how the performance of tool users can be impacted by a ‘fit’ between their tasks and the technology.

The purpose of this chapter is to discuss the theoretical underpinnings of the Technology-Performance Chain (TPC) model addressing the study’s objectives to examine the impacts of ‘fit’ on mHealth tool use and CHW performance, the impact of mHealth tool use on CHW performance, and the impact of precursors of use on mHealth tool use. First, the origins and evolution of Task-Technology Fit (TTF) and Technology-to-Performance Chain (TPC) theories are discussed. Second, prior scholarly contributions are highlighted and their shortcomings are identified. Third, the implications of these shortcomings for the present study are derived.

4.2 The Theory of Task-Technology Fit (TTF)

The theory of Task-Technology Fit (TTF) can be traced to the perspectives of ‘Cognitive Fit’ (Vessey, 1991; Vessey and Galleta, 1991; Vessey, 1994), and ‘Task-System Fit’ (Goodhue, 1992; Goodhue, 1994). These two theoretical foundations of the fit concept are important.

4.2.1 Cognitive Fit

Vessey (1991) examined the ‘Cognitive Fit’ between a task and its mental representation, to influence individual performance in problem-solving (p. 221). The central premise of Cognitive Fit is that problem-solvers must use processes that match problem representations. The generic model upon which this ‘fit’ perspective is premised is depicted in Figure 4.1.

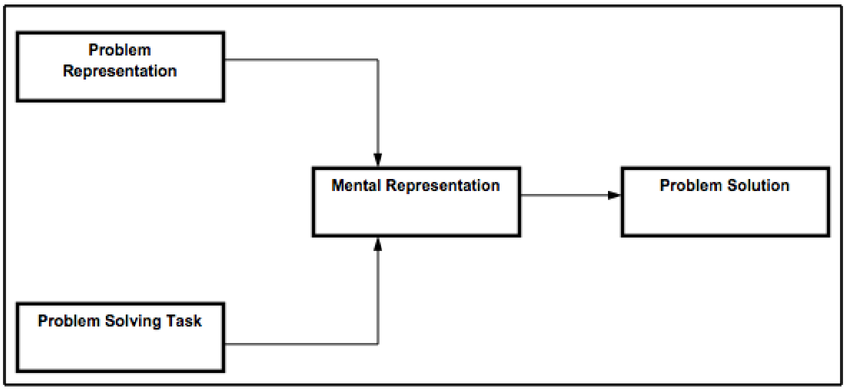

Figure 4.1. Generic Problem-Solving Model (Vessey, 1991, p. 221)

‘Problem-solution’ is the performance outcome of the relationship between ‘problem representation’ and ‘problem solving task’. The ‘mental representation’ is a consequence of a Cognitive Fit between ‘problem representation’ and ‘problem-solving task’ characteristics. These characteristics then match for a ‘problem-solution’. Vessey and Galleta (1991) presented a variation of the generic problem-solving model, incorporating a match between ‘problem-solving skill’ and the task or problem representation. This extension of the generic problem-solving model is depicted in Figure 4.2.

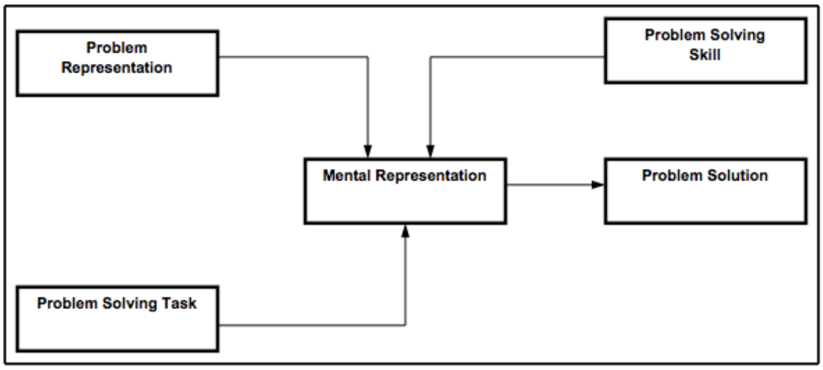

Figure 4.2. Extended Problem-Solving Model (Vessey and Galletta, 1991, p. 67)

The matching of ‘problem representation’, ‘problem-solving task’, and ‘problem-solving skill’, leads to a ‘Cognitive Fit’, which is expected to increase problem-solving performance (Vessey and Galleta, 1991). However, a mismatch between these characteristics would lower performance (p. 66). The ‘Cognitive Fit’ perspective preceded the theory of ‘Task-System Fit’, discussed next.

4.2.2 Task-System Fit

Goodhue (1992) defined 'Task-System Fit' as the degree to which an information system or systems environment assists users in performing their tasks. This perspective is also described as the 'Fit' between task requirements and the functionality of the Information Systems (IS) environment (p. 304). 'Task-System Fit' is based on the Theory of Information Systems (IS) 'Satisfactoriness' (Goodhue, 1988), which was derived from the concepts of 'job satisfaction' and 'individual satisfactoriness', which were components of the Theory of Work Adjustment (Dawis, Lofquist and Weiss, 1968). Goodhue (1988) made four important observations, in understanding Task-System Fit. First, 'IS satisfaction' implicitly relates to 'job satisfaction' (Bailey and Pearson, 1983). 'Job satisfaction' may not necessarily be strongly linked to performance (Iaffaldano and Muchinsky, 1985). However, user evaluations of IS are considered similar or dissimilar to 'job satisfaction', and could be strongly or weakly linked to performance. Second, to better understand user evaluation of IS, Dawis et al. (1968) defined the difference between 'job satisfaction' and 'individual satisfactoriness'. 'Job satisfaction' was described as the extent to which the system used meets an individual's personal needs. 'Individual satisfactoriness' was described as the extent to which user abilities meet task requirements. Third, Goodhue (1988) proposed distinguishing between the concepts of 'job satisfaction' and 'IS satisfaction', a similar approach to articulating the difference between ''job satisfaction' and 'individual satisfactoriness' (Dawis et al., 1968). In evaluating the 'satisfactoriness' of IS, users must assess how well the system meets their personal needs. Goodhue (1988) contended that multiple user evaluations could blur the distinction between task requirements and personal needs, thereby representing less clear linkages with performance. He postulated that user evaluations of systems based on a 'Task-System Fit' would more closely link with task performance, and must, therefore, be considered. Goodhue's (1988) 'Task-System Fit' Model is depicted in Figure 4.3. Causes of 'Task-System Fit' can be identified as the system and task, both of which are moderated by individual abilities.

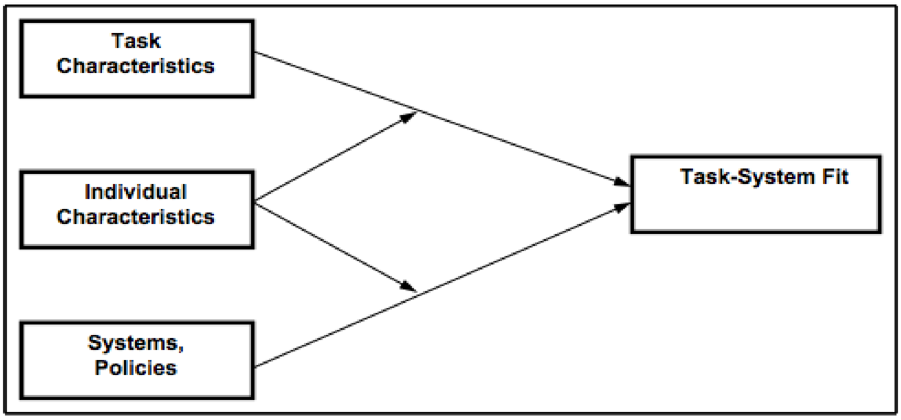

Figure 4.3. Task-System Fit Model (Goodhue, 1988)

He posited that all being equal, changes to tasks that require the user to impose greater demands on the systems environment should lead to a decrease in ‘Task-System Fit’. Similarly, changes to the systems environment (more suitable functionality or policies) as needed to perform the tasks at hand, should enhance ‘Task-System Fit’. In essence, ‘the ‘system’ used must be defined to suit the ‘task’ being supported. The notion of ‘Task-System Fit’ preceded the theoretical perspective of Task-Technology Fit (TTF), discussed next.

4.2.3 Task-Technology Fit (TTF)

In IS research, the concept of Task-Technology Fit (TTF) has assumed various definitions. The numerous TTF definitions that have been used in TTF research are summarized in Table 4.1.

Table 4.1. Definitions of Task-Technology Fit (TTF)	
Definition	Source
The degree to which available technology is useful in supporting the unique needs of a given task.	Nance (1992, p. 50)
The degree to which technology assists an individual in performing his or her portfolio of tasks.	Goodhue and Thompson (1995, p. 216)
The degree to which a technology does or could meet user needs.	Goodhue, Littlefield and Straub (1997, p. 458)
The matching of the functional capability of available information technology with the activity demands of the task at hand.	Dishaw (1994, p. 36), Dishaw and Strong (1998, p. 154)
The extent to which tasks can be performed effectively and efficiently using particular technologies.	Mathieson and Keil (1998, p. 222)
User perceptions of the fit of systems and services used based on personal task needs.	Pendharkar, Khosrowpour and Rodger (2001, p. 84)
The match or congruence between an information system and its organizational environment.	Klaus et al (2003, p. 106)
The extent to which technology provides features and fits requirements of the task.	Lippert and Forman (2006, p. 275)
The perception that system capabilities match user task requirements.	Jarupathirun and Zahedi (2007, p. 945)
The degree to which an organization's information systems functionality and services meet information needs of the task.	Wu, Shin and Heng (2007, p. 168)

Ioiomo and Aronson (2003) observed that as the gap between task requirements and technological support capacity increases, 'Fit' significantly decreases (p. 197). This gap signifies an 'under-fit' or 'over-fit'. An 'under-fit' represents minimal capacity because the technology used does not sufficiently meet task requirements and is rendered ineffective. Conversely, an 'over-fit' represents excessive technological support capacity because the technology provides excessive resources, thereby causing IT 'slack' (Gupta, 2003). Thus 'fit' technology represents sufficient supporting capacity to meet user needs (Nance and Straub, 1996). Since the inception of TTF theory, a clear distinction between research at the individual and group levels has been observed. At the individual level, survey methods have often been used. For example, to assess impacts of TTF on utilization and performance outcomes, Goodhue (1998) surveyed 357 technology users across ten companies. However, at the group level, experimental studies have often been conducted. For example, Fuller and Dennis (2004) conducted a longitudinal experiment to assess TTF effects on group performance. As such, TTF can be used to link observed occurrences at the individual and group level, to utilization and performance outcomes.

TTF models comprise the task and technology, and the ‘fit’ between task and technology characteristics, which in turn affects technology use and/or task performance outcomes (Goodhue, 1995; Goodhue and Thompson, 1995; Dishaw and Strong, 1998a; Dishaw and Strong, 2003; Dishaw, Strong, and Bandy, 2002; Strong, Dishaw and Bandy, 2006). TTF influences use because an IT will be used if its functions ‘fit’ user needs (Dishaw and Strong, 1998a, p. 153). Similarly, TTF influences user performance because a task will be performed if functions of the IT used ‘fit’ user needs (Goodhue, 1995, p. 1829).

The task performed by the technology user is the first Task-Technology Fit (TTF) component. A task is an action a performer needs to perform in order to accomplish a goal or influence an outcome (Hackman, 1969; Hackos and Redish, 1998; Hansen, 1999; Shepherd, 1998). In prior works, four task types have been identified and used to evaluate decision processes (Hackman, 1969; Wood, 1986, p. 61). These task types are classified in Table 4.2.

Table 4.2. Task-Types

Task Type	Description	Source(s)
Task Qua Task	Tasks are defined as a pattern of stimuli impinging on the task performer. Task characteristics are objective “real world” properties such as the physical nature of either the stimuli e.g. input rate, or stimulus material e.g. instructions.	Roby and Lanzetta, 1958; McGrath and Altman, 1966
Task as Behaviour Requirements	Tasks are defined as the behavioural responses of the task performer to achieve a specified level of performance. Task characteristics are specific behavioural requirements, needs, or ‘critical demands’, i.e. required or needed for adequate performance.	Miller, 1962; Gagne, 1964
Task as Behaviour Description	Tasks are defined as a group of job-oriented technological processes e.g. recording, or human behaviours e.g. decision-making that the performer would typically exhibit when performing the task.	McCormick 1965; Dunnette, 1966
Task as Ability Requirements	Tasks are defined as a specific pattern of abilities or characteristics i.e. skills, required of the task performer for successful task completion based on physical, psychological and background characteristics.	Ferguson, 1956; Fleishman and Hogan, 1978;

In the domain of TTF research, tasks have often been characterized as behaviour ‘requirements’ (Miller, 1962; Gagne, 1964), or ‘description’ (McCormick, 1965; Dunnette, 1966). For the most part, the task has been defined as an action to be performed by a technology user (Nance, 1992). This performed task has been described as the 'behavioural requirements' that are necessary for accomplishing a stated goal through a process, given the information available (Zigurs and Buckland, 1998, p. 316). The 'behaviour requirement' task-type is considered a relatively stable attribute of any task, and can be described independently of the characteristics of the task performer (Wood, 1986). Moreover, since tasks are activities performers need to perform, required behaviours are influenced by the nature of the task, not the characteristics of the performer. This task type therefore represents a sound basis for task description (Hackman, 1969). As such, it is has been considered the most applicable approach to IS research (Junglas, Abraham and Watson, 2008). The task performed can therefore comprise characteristics that reflect the performer's behavioural requirements, needs, or critical job demands (Hackman, 1969, p. 104). Tasks can be characterized along dimensions such as routineness versus non-routineness (Perrow, 1967), interdependence (Wageman and Gordon, 2005), variety (Karimi, Somers and Gupta, 2004), time criticality (Ballard and Siebold, 2004), user mobility (Gebauer et al., 2010), and location dependency (Yuan et al., 2010). These characteristics of a task, typically used in IS research, are described in Table 4.3.

Table 4.3. Typical Task Characteristics

Task characteristic	Description	Source
Routineness Versus Non-Routineness	The need of the task performer for structuredness, difficulty, and predictability in performing the task.	Gebauer, Shaw and Gribbins (2010)
Interdependence	The need of the task performer to co-operate with others in preforming the task.	Wageman and Gordon, 2005; Hsiao and Chen (2012)
Time criticality	The need of the task performer to urgently perform the task.	Ballard and Siebold, 2004; Gebauer and Tang, 2007
Mobility	The need of the task performer for manoeuvrability in performing the task.	Gebauer, Shaw and Gribbins (2010)
Location Dependency	The need of the task performer to know his or her location and the location or positioning of physical objects.	Yuan, Archer, Connelly and Zheng (2010)
Information Seeking	The need of the task performer to acquire information to fill a knowledge gap.	Wilson, 2000; Case 2012

The technology used by the task performer is the second component of Task-Technology Fit (TTF). Technology is the system or tool (hardware, software, or data) used by a user to perform a task (Goodhue, 1995). This system or tool can be computerized or paper-based[31], and encompasses procedures, equipment, and knowledge or information transfer (Randolph, 1986; Ammenwerth et al., 2006, p. 4). The technology is described as providing a set of features that influences how the user chooses to perform a particular task (DeSanctis and Poole, 1994). In the Operations Management discipline, three types of technology have been identified in previous research. Technology has been classified as operations, materials, or knowledge (Hickson, Pugh, Pheysey, 1969, p. 380), as summarized in Table 4.4.

Table 4.4. Technology Types

Technology Type	Description	Source(s)
Operations Technology	Technology is defined as the techniques used in sequencing workflow activities to produce and distribute output i.e. desired goods or services.	Thompson and Bates, 1957; Pugh, Hickson Hinings, Macdonald, Turner and Lupton, 1963
Materials Technology	Technology is defined as the characteristics of particular objects or raw materials or used by users in workflow activities.	Perrow, 1967; Thompson, 1967
Knowledge Technology	Technology is defined as the characteristics of particular knowledge or information attributes useful to users in workflow activities.	Hickson, Pugh and Pheysey (1969)

In more recent research, two basic groups of Information Technologies (ITs) have been identified (Huber, 1990). The first group, described as 'basic characteristics', relates to data storage, transmission, and processing capacities. Advanced ITs could enable higher levels of these characteristics. Notably, no clear distinction has been made between data (stimuli and symbols), and information (data that conveys meaning as a result of reducing uncertainty) (p. 49). The second group, described as 'properties', relates to the multi-faceted configuration of levels that characterize those technologies most relevant to particular tasks. These may cause the use of advanced ITs to have effects on users (p. 50). In prior IS research, ITs have been characterized along attributes related to communication and decision aiding, information codification, and information diffusion (Huber, 1990; Simons, 1995; Wickramasinghe, 1999). These technology characteristics are described in Table 4.5.

[31] Please refer Chapter 3 for empirical comparisons of mHealth tool and paper-based system user performance impacts.

Table 4.5. Typical Technology Characteristics		
Technology Characteristic	Description	Source(s)
Communication	IT enables easier, more reliable, and less costly, means of communication, and recording and indexing of content.	Huber, 1990
Decision Aiding	IT enables the storing and retrieval of large amounts of data, the rapid and selective access to, and accurate combination and reconfiguration of, information.	Huber, 1990
Information Codification	IT enables the structuring of information through the categorization (codifying) and compression of raw data.	Boisot, 1986; Simons, 1995
Information Diffusion	IT enables easy information sharing by providing efficiently and effectively codified channels for diffusing data.	Simons, 1995

In related IS research, technology has been assessed along information characteristics such as accuracy, timeliness, relevance, aggregation, formatting, uniqueness, conciseness, clarity, and readability (Swanson, 1974; Ahituv, 1980; DeLone and McLean, 1992). Technology has similarly been characterised as system and information quality (DeLone and McLean, 2003). System quality refers to desired processing characteristics of technology such as usability, reliability, and response time, whereas information quality refers to desired content characteristics such as completeness, accuracy, format, and currency (p. 25). In TTF-related research, technology features evaluated have closely resembled so-called IT 'properties' (Huber, 1990), typically consistent with characteristics such as communication and decision aiding (p. 50). For instance, for communication, these properties have included facilitating the ITs used in (1) transmitting precise information easily, cost-effectively, rapidly, and across time and geographic location (Rice and Bair, 1984), and (2) recording and indexing information content more reliably (Culnan and Markus, 1987). For decision aiding, these properties have included facilitating the users of ITs in (1) quickly and cost-effectively storing and retrieving large amounts of information, (2) more rapidly and selectively accessing the most recent information generated, and (3) more accurately combining, re-configuring, and transmitting information for interpretation and use (Zmud, 1983; Sprague and McNurlin, 1986; Sprague and Watson, 1986). In prior works, the 'fit' variable in TTF models has been theorized to influence outcomes of use (e.g. Dishaw and Strong, 1998a; Dishaw and Strong, 2003, Strong et al., 2006), user performance (e.g. Goodhue, 1995, Goodhue et al., 2000), or a combination thereof (e.g. Goodhue and Thompson, 1995). In TTF research, the use of technologies has involved hardware such as Electronic Performance Support Systems (Tjahono, Fakun, Greenough and Kay, 2001), software such as UML (Grossman, Aronson and McCarthy, 2005) data such as web travel information (D'Ambra and Wilson, 2004a, 2004b), and user-support services such as voice recognition (Goette, 2000). The performance of tasks involves but is not restricted to user activities such as intellective tasks such as solving problems with correct responses (Murthy and Kerr, 2004), decision-making such as evaluating criteria (Fuller and Dennis, 2009), and software maintenance such as de-bugging administrative systems and applications (Dishaw and Strong, 1998a). The TTF theoretical model, and its variations and extensions, are identified and discussed in Section 4.3.

4.3 The Evolution of the Task-Technology Fit (TTF) Model

In building on the theoretical perspectives of 'Task-System Fit' and 'Cognitive Fit', Goodhue (1995) and Goodhue and Thompson (1995) proposed two distinct albeit related general models representing the concept of TTF. Goodhue (1995) proposed a TTF as User Evaluation (UE) model based on users perceptions of the degree to which systems characteristics match their task needs (p. 1827).

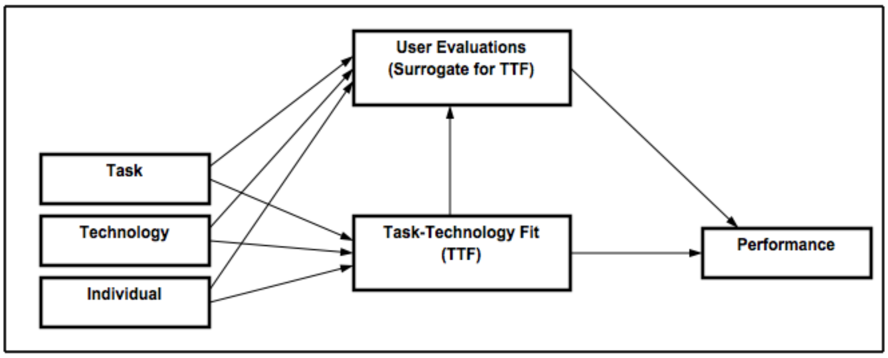

Figure 4.4. User-Evaluation (UE) Model (Goodhue, 1995, p. 1830)

As per this model (Figure 4.4), users will evaluate the characteristics of the system used and the degree to which it meets their task needs and abilities (TTF), which are presumed to lead to higher levels of task performance. If users utilize a technology in performing specific tasks, then they are capable of evaluating its TTF from personal experience. As such, higher user evaluations of TTF will lead to increased performance levels (Goodhue, 1995, p. 1830). At the same time, Goodhue and Thompson (1995) posited that utilization and performance impacts will result from a Task-Technology Fit (TTF). As such, a 'fit' between the task and technology occurs when the technology has features or support that 'fit' task requirements (p. 214). This 'fit' relationship is depicted in Figure 4.5.

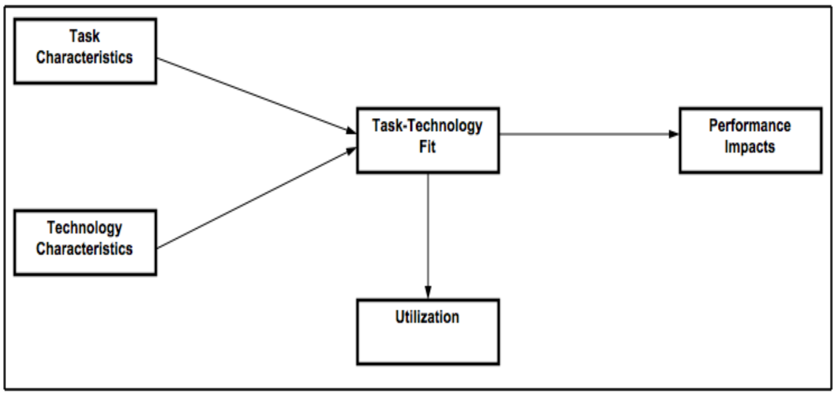

Figure 4.5. Basic (Fit-Focus) Task-Technology Fit (TTF) Model (Goodhue and Thompson, 1995, p. 215)

In this basic (Fit-Focus) model[32], which is the basis for the modeling of TTF, 'fit' is linked to the outcomes of utilization and performance (Goodhue and Thompson, 1995). Information systems have been observed and are expected to positively impact technology utilization and performance outcomes when there is correspondence between technological functionality and the user's task requirements (p. 214). This model indicates that use and user performance outcomes are together, consequences of a 'fit' between task and technology. As such, in performing the task, the technology is utilized. In essence, to perform the task, there must be a 'fit' between the task and technology. In addition, to use the technology, this 'fit' must be present. In later work, Dishaw and Strong (1998a) emphasized that Information Technology (IT) will be used and provide benefits if its functions support the activities of the user, and proposed a basic model of 'TTF and Utilization' (p. 153). This model shows TTF as the independent variable and utilization as its outcome. This was a linear model, as depicted in Figure 4.6.

Figure 4.6. Task-Technology Fit (TTF) and Utilization Model (Dishaw and Strong, 1998a, p. 153)

[32] This 'Fit-Focus' is evident in 'Cognitive Fit' research on the impact of graphs versus tables on individual decision-making performance (Vessey, 1991).

This model is based on the premise that a higher 'fit' leads to user expectations of beneficial consequences of use. The TTF construct captures task, technology, and individual characteristics, and their matching. However, in an expanded TTF model, these characteristics can be included and shown to affect a 'fit' variable (Dishaw and Strong, 1998a). In subsequent work, Dishaw, Strong and Bandy (2002) developed a TTF model integrated with the Technology Acceptance Model (TAM).

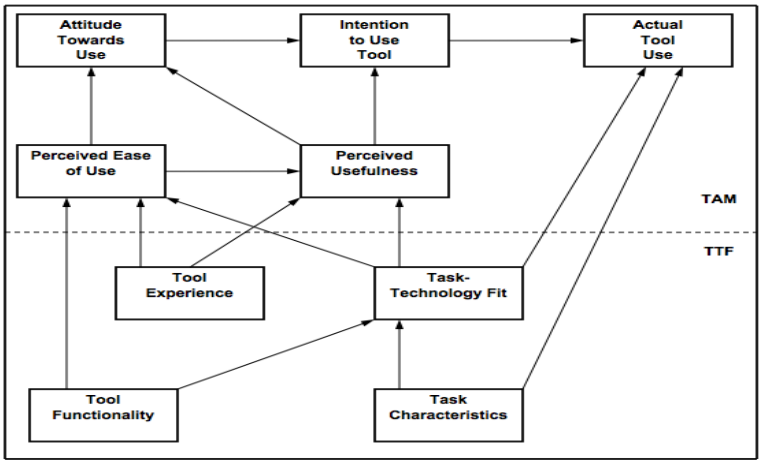

Figure 4.7. Task-Technology Fit (TTF) Integrated with Technology Acceptance Model (TAM) (Dishaw, Strong and Bandy, 2002, p. 153)

The TAM and TTF constructs depicted in Figure 4.7 were combined to capture two alternative perspectives of users choices to utilize ITs. The TAM is premised upon beliefs and attitudes as determinants of IT use, whereas TTF is based on users choosing to use ITs that provide benefits such as improved performance, irrespective of their attitudes (Goodhue, 1995). In a subsequent study, Strong, Dishaw and Bandy (2006) developed a TTF model, in which the task performed affects the utilization of the technology, depending on the levels of rendered technological support for the task being supported. This model captures TTF as the capacity of the IT used to support the task performed (Goodhue and Thompson, 1995). The model is depicted in Figure 4.8.

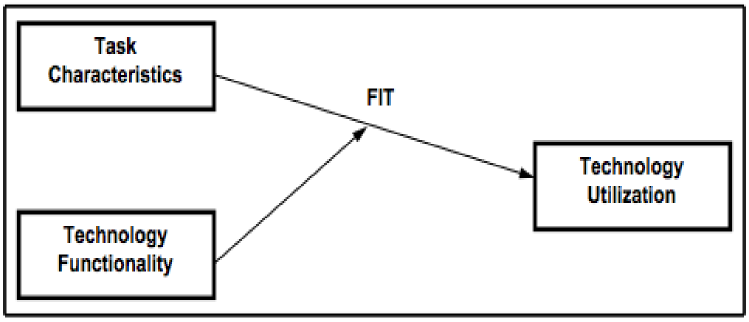

Figure 4.8. Task-Technology Fit (TTF) Model (Strong, Dishaw and Bandy, 2006, p. 97)

This model has been extended by including the construct of 'Computer Self-Efficacy' (CSE), which has been defined as a judgement of the technology user's ability to use a computer (Compeau and Higgins, 1995). This model was extended on the basis that TTF, which is premised upon a rational approach to use, may not itself sufficiently capture utilization choices, which may be affected by characteristics of the individual user (Strong, Dishaw and Bandy, 2006, p. 97). This extended basic TTF model is depicted in Figure 4.9.

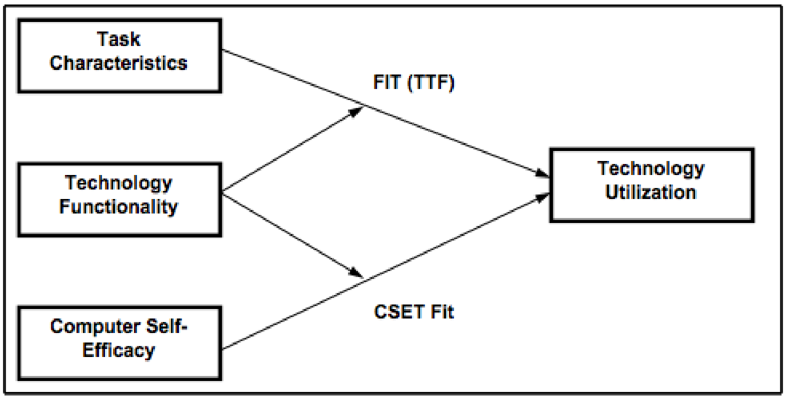

Figure 4.9. Extended Task-Technology Fit (TTF) Model (Strong, Dishaw and Bandy, 2006, p. 99)

The extended TTF model shows that utilization is affected by users' judgement of their ability to use ITs, as moderated by the characteristics of the technology that is appraised. Since the introduction of the TTF model in the mid 1990s, and its subsequent variations and extensions, the 'fit' construct has been operationalized in various ways. This operationalization of the 'fit' construct in TTF research is discussed in Section 4.4.

4.4 The Operationalization of Fit in Task-Technology Fit (TTF) Research

In TTF research, a variety of TTF constructs have been proposed, developed, and examined. In prior works, the TTF construct has been operationalized using two distinct approaches.

First, the construct of TTF has mostly been operationalized as ‘user-evaluated’ or ‘perceived’. A notable example is Goodhue’s (1995) operationalization of TTF as comprising user evaluations of twelve dimensions.

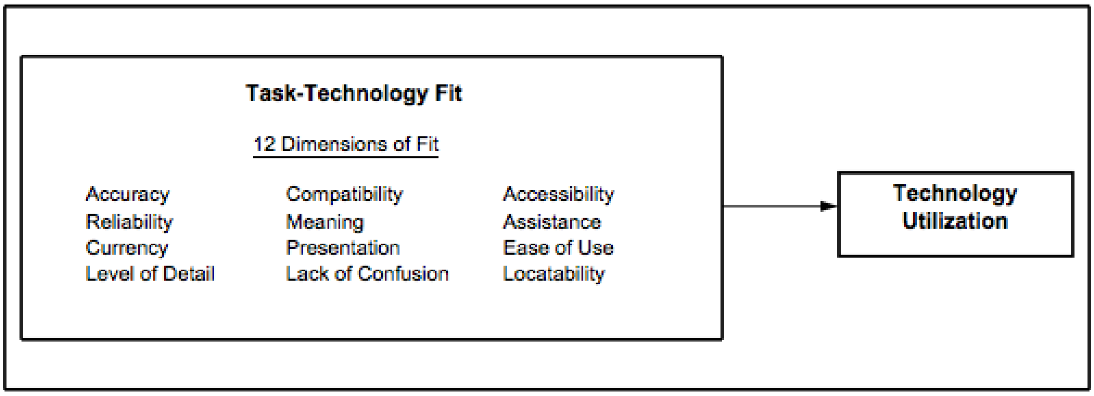

Figure 4.10. Operationalization of Basic Task-Technology Fit (TTF) Model (Goodhue, 1995)

Goodhue and Thompson (1995) argued that this approach to operationalizing TTF could be generally applied to any combination of information systems, tasks, and users, and supported their assertion by empirically examining these twelve ‘fit’ dimensions (Figure 4.10). In addition to proposing their basic model of ‘TTF and Utilization’ (Figure 4.6), Dishaw and Strong (1998a) operationalized TTF as a ‘Fitness-for-Use’ (FFU) construct (p. 157). This operationalization is similar to Goodhue’s (1995) ‘user evaluation’. The difference, however, is that technology characteristics and task needs are evaluated in terms of the ‘quality’ of technology, and in terms of whether or not it is ‘fit’ for user purposes.

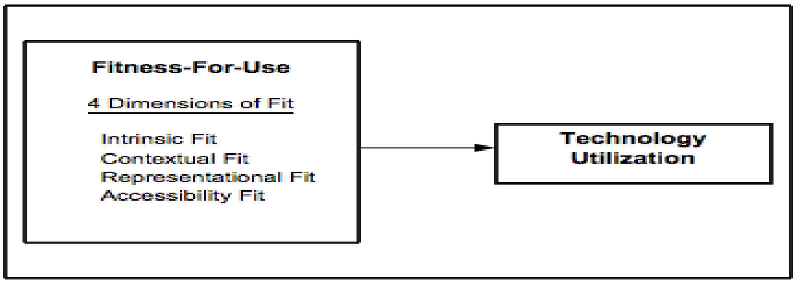

Figure 4.11. Operationalization of Basic Fit-For-Use (FFU) Model (Wang and Strong, 1996)

TTF was operationalized as fifteen dimensions grouped as four categories, classified as ‘intrinsic’, ‘contextual’, ‘representational’, and ‘accessibility’ (Dishaw and Strong, 1998a, p. 158), based on Wang and Strong’s (1996) research on ‘data fitness’ for users (Figure 4.11).

Second, the construct of TTF has been operationalized as a ‘computed interaction’ or equivalent ‘difference score’. Dishaw (1994) operationalized TTF as a result of the correspondence between task and technology factors, and computed ‘fit’ as a difference score as follows:

$$Fit = f\,(task,\ technology,\ |\ task - technology\ |)$$

‘Fit’ is a function of the task, the technology, and the correspondence between the task and technology. An instrument was used to measure task and technology dimensions, and these measures used to calculate a ‘fit’ between the task and technology (Dishaw, 1994, p. 60). Dishaw and Strong (2003, p. 7) operationalized TTF as the ‘interaction’ between task and technology factors, and computed a ‘fit’ interaction term as follows:

$$Fit = f\,(task * technology)$$

‘Fit’ is a function of the task, the technology, and the interaction between task and technology. Dishaw and Strong (1998b) used this expression to calculate a ‘fit’ between dimensions of the task and technology measured using an instrument (p. 114). Strong, Dishaw and Bandy (2006) operationalized TTF as the interaction between the task and technology and Computer Self-Efficacy Fit (CSE Fit), as the interaction between the technology and CSE (Figure 4.9). These interactions are depicted in Figure 4.12.

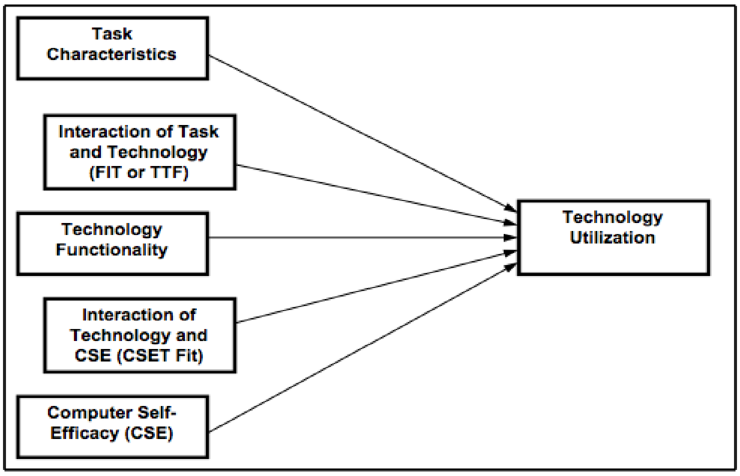

Figure 4.12. Extended Task-Technology Fit (TTF) Model Interactions (Strong, Dishaw and Bandy, 2006)

Task and technology characteristics are shown to have direct effects on utilization. These task and technology characteristics are also shown to interact to affect utilization (Strong et al., 2006). Technology characteristics and CSE also directly affect utilization. In addition, the interaction between these variables has an effect on utilization (p. 100). The operationalization of the ‘fit’ construct as described in the above studies, is represented in a number of notable previous studies on the impacts of TTF, as summarized in Table 4.6.

Table 4.6. Operationalization’s of Fit in Task-Technology Fit (TTF) Research

Model Constructs	Operationalization(s) of Fit	Design	Source
Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Intention to Use, Actual Use, Task, Technology, Fit	Computed Difference Score (|Task – Technology|), User Evaluation	Survey	Dishaw (1994)
Task, Technology, Fit, Performance, Computer Literacy	User Evaluation	Survey	Goodhue (1995)
Task, Technology, Fit, Utilization, Performance	User Evaluation	Survey	Goodhue and Thompson (1995)
Fit, Utilization	User Evaluation	Experiment	Dishaw and Strong (1998a)
Task, Technology, Fit, Utilization	Computed Interaction (Task * Technology)	Survey	Dishaw and Strong (1998b)
Task, Technology, Fit, Utilization, Task Experience, Technology Experience	Computed Interaction (Task * Technology)	Survey	Dishaw and Strong (2003)
Task, Technology, Fit, Utilization, Computer Self Efficacy	Computed Interaction (Task * Technology)	Survey	Strong, Dishaw and Bandy (2006)

In subsequent works, the operationalization of TTF as user evaluation (UE) has mostly been adopted (for example D’Ambra and Wilson, 2004a, 2004b). However, in fewer works, TTF has been operationalized as computed interaction (for example Teo and Men, 2008). In these works, TTF theory has been applied to various contexts in which various technologies have been used in diverse task domains. This application of TTF theory to various contexts is discussed in Section 4.5.

4.5 The Application of Task-Technology Fit (TTF) Theory

TTF theory has been applied to study users in organisational contexts such as electronic procurement (e-Procurement) (Gebauer and Shaw, 2004), Knowledge Management (KM) systems (Lin and Huang, 2008, 2009), and manufacturing (Lippert and Forman, 2006). TTF theory has also been applied to study IT service consumers such as airline travellers using Online (Web) Information Systems (D'Ambra and Wilson, 2004a, 2004b), and students using Online (Web) Shopping Websites (Klopping and McKinney, 2008), and more recently to the contexts of Mobile Information Communication Technologies (MICTs) such as health care in hospital settings (Junglas, Abraham and Ives, 2009), and Mobile Banking (m-Banking) service systems (Zhou, Lu and Wang, 2010). These and various other contexts to which TTF theory has been applied are summarized in Table 4.7.

Table 4.7. Applications of Task-Technology Fit (TTF) Theory		
Context		**Source(s)**
Task Domain	**Technology Domain**	
Nursing Patient Care in Hospitals	Mobile Information Communication Technologies (MICTs)	Junglas, Abraham and Ives (2009)
Electronic Procurement (e-Procurement)	Mobile Business Applications	Gebauer and Shaw (2004)
Computer-Mediated Communication	Group Support Systems (GSSs)	Shirani et al (1999)
Information Processing and Decision-Making	• Graphic User Interfaces (GUIs) • Database Management Systems (DBMSs)	Mathieson and Keil (1998)
Cognitive and Coordination for Problem-Solving	Group Support Systems (GSSs)	Fuller and Dennis (2009)
Knowledge Processing	Knowledge Management Systems (KMSs)	Hahn and Wang (2009)
• Computer Access • Environment Control • Word Processing	Voice Recognition Technology (VRT)	Goette (2000)
Academic	Integrated Information Center (IIC) Technology	Lending and Straub (1997)
Accessing Information for International Travel	Online (Web) Information Resource System	D'Ambra and Wilson (2004a, 2004b)
Knowledge Creation, Storage, Retrieval, Transfer, and Application	Knowledge Management Systems (KMSs)	Lin and Huang (2008, 2009)
Field Mobile Computing for Policing and Law Enforcement	Mobile Computer Information System Devices	Ioimo and Aronson (2003)
Software Development	Unified Modeling Language (UML)	Grossman et al (2005)
Electronic Commerce (e-Commerce)	Consumer Online (Web) Shopping Websites	Klopping and McKinney (2004)
Manufacturing of Parts, Components, and Assemblies	Collaborative Visibility Network (CVN) Supply Chain System	Lippert and Forman (2006)
Consulting	Knowledge Management Systems (KMSs)	Teo and Men (2008)
Port Industry Operations and Services	Internet	Norzaidi, Chong, Murali and Salwani (2007); Norzaidi, Chong, Murali and Salwani (2009)
Mobile Banking (m-Banking)	Mobile Banking (m-Banking) Services	Zhou, Lu and Wang (2010)
Information Processing for Hospitality Services		Zhou, Guoxim and Lam (2009)
Manufacturing Operations	Task Support System (TSS)	Tjahjono, Fakun, Greenough and Kay (2001)
Clinical Healthcare	Health Information Systems (HISs)	Pendharkar, Khosrowpour and Roger (2001)
Nursing Patient Care in Pediatric Hospitals	Health Information Technology (HIT)	Karsh, Holden, Escoto, Alper, Scanlon, Arnold, Skibinski and Brown (2009)
Patient Care in a Health Centre	Electronic Health Record (EHR) System	Willis, Gayar and Deokar (2009)
Clinical Health Care	Electronic Medical Record (EMR) System	Kilmon, Fagan, Pandy and Belt (2008)
Clinical Tasks	Nursing Information Systems	Lin (2008)

Despite the widespread application of TTF theory, TTF research has had notable shortcomings. These shortcomings in the application of TTF theory are discussed in Section 4.6.

4.6 Shortcomings in Task-Technology Fit (TTF) Research

4.6.1 Task Characteristics

In some prior works, tasks have not been distinguished from their underlying characteristics. For example, Klaus, Gyires and Wen (2003) studied the 'Fit' of web information systems to the non-work activities of searching, purchasing, and entertainment (p. 110). However, it was not clear whether these activities were tasks or their characteristics. In some works, tasks and their underlying characteristics are distinguishable from each other. However, it is not clear how the identified characteristics reflect tasks performed. For example, in a study on the use of mobile technologies for mobile locatability, Junglas, Abraham and Watson (2008) defined tasks as behaviour requirements. However, in evaluating the task dimensions of 'location sensitiveness and insensitiveness', they did not clarify why these characteristics were behaviour requirements. Such a lack of separation between the task construct and its characteristics is a problem for TTF research. This is because without specified characteristics, it becomes difficult to evaluate the needs, requirements, or demands of the task performer. Moreover, task attributes must be observed relative to technology characteristics. In light of the above, the following implications for task specification in TTF research are derived for the present study:

1. The task performed must be clearly described.
2. The characteristics of this task must be specified.
3. These characteristics must represent the described task.

4.6.2 Technology Characteristics

As with tasks, in some prior works, technologies have not been distinguished from their characteristics. For instance, in a study of web usage for information tasks, D'Ambra and Wilson (2004a) categorized hardware and software tools as technology characteristics (p. 298). However, these descriptions should be used to describe technologies, not characteristics. In some studies, technologies and their underlying characteristics are differentiated. However, even in these studies, it has not always been apparent how the characteristics identified reflect the technologies used. For instance, in a study on port industry managers, Norzaidi, Chong, Murali and Salwani (2007) defined the intranet technology characteristics as ‘social presence’, ‘concurrency’, ‘physical interface’, and ‘communication immediacy’ (p. 1231). However, they did not explain how these characteristics represented intranet technology. As with the task component discussed in Section 4.6.2, a lack of separation between the technology construct and its underlying characteristics is problematic for TTF research. This is because without specified characteristics, it becomes more difficult to appraise functions or support features of the technology being used. Thus the following implications for technology specification in TTF research are derived for the present study:

1. The technology used by the user must be clearly described.
2. The characteristics of this technology must be specified.
3. These characteristics must represent the described technology.

4.6.3 The Fit between Task and Technology Characteristics

TTF researchers do not always expound on the concept of a ‘fit’ between task and technology characteristics as the presence of functional support for particular user needs. For example, D’Ambra, Wilson and Akter (2013) conducted a study on electronic book (e-book) usage. First, task characteristics were specified as ‘teaching’ and ‘research’. Second, technology characteristics were specified as ‘platform’ and ‘content’. Consequently, their ‘fit’ was theorized (p. 51). There was, however, no sufficient explanation as to how ‘teaching’ and ‘research’ must necessarily ‘fit’ with ‘platform’ and ‘content’. As such, ‘fit’ did not clearly represent e-book support functions for academic tasks. In other work, Chang (2008) conducted a study on IT usage for web-based auction processes. First, the auction task characteristics ‘price negotiation’ and ‘item acquisition’ were specified. Second, the technology characteristics ‘autonomy’, ‘continuity’, ‘adaptivity’, ‘goal orientation’, ‘learning ability’, and ‘communication’ were specified. As such, a ‘fit’ between these characteristics comprising eight dimensions was theorized. However, a ‘fit’ of technology to task needs was not explicated. Such a lack of explanation for the relevance of technology characteristics to tasks poses a problem for TTF research because a ‘fit’ is purported and yet remains unspecified. The following implications for the conceptualization of ‘fit’ are thus derived:

1. The relationship between the task performed and the technology used must be specified such that a ‘fit’ between their underlying characteristics is observable.
2. In doing so, a ‘fit’ between technological support and task needs is adequately represented.

Subsequent to correctly specifying task and technology characteristics and a ‘fit’ between these characteristics, it is important to ensure consistent theorizing and testing of this ‘fit’. One way to ensure this is by specifying the ‘fit’ perspective adopted to test its impacts (Venkatraman, 1989). The use and utility of ‘fit’ perspectives is discussed next.

4.6.4 The Importance of Fit Perspectives in Task-Technology Fit (TTF) Research

Blalock Jr (1965) argued that a lack of correspondence between ‘fit’ concepts and underlying mathematical formulations could weaken the link between theory and testing. Two decades later, Venkatraman (1989) observed that ‘fit’ concepts were seldom tested in precisely the manner theorized (p. 438), and proposed that ‘fit’ models should be tested using multiple techniques, each representing a distinct perspective of ‘fit’ theory. More recently, Bergeron, Raymond and Rivard (2001) suggested that future researchers ought to theorize ‘fit’ concepts in a manner consistent with their empirical analysis (p. 125). To date, the theorizing and testing of ‘fit’ concepts has remained rather inconsistent. The adoption of ‘fit’ perspectives in context would be most useful for evaluating the various ways in which task and technology characteristics come to affect use and user performance. Moreover, a mechanism can be identified to better articulate these impacts. Furthermore, the components of TTF can be assessed without re-specification. As articulated in Sections 4.6.2 to 4.6.4, TTF researchers have not sufficiently specified task and technology characteristics, and the ‘fit’ between these characteristics. Consequently, it is not possible to operationalize TTF using ‘fit’ perspectives (Venkatraman, 1989). As such, the adoption of ‘fit’ perspectives without succinctly theorizing a ‘fit’ between task and technology characteristics signifies a mis-specification. The proper specification of these underlying characteristics is, therefore, fundamental, and to give guidance on whether ‘fit’ is best examined as a user evaluation or as a computed interaction, among other approaches. With such specificity, ‘fit’ perspectives would strengthen TTF theory, and as such, has three advantages:

1. The theorizing and testing of TTF is consistent.
2. The evaluation of varying use and user performance TTF effects is simplified.
3. If correctly specified, a uniform set of task and technology characteristics are usable.

4.6.5 Use and User Performance as Outcomes of the Fit between Task and Technology Characteristics

In the basic 'Fit-Focus' TTF model (Goodhue and Thompson, 1995), 'fit' was theorized to influence use and user performance (Figure 3.5). However, use was not linked to user performance. Thus Goodhue and Thompson (1995) proposed its inclusion and argued that adding use would signify a better understanding of performance. The model was extended so that TTF was linked to user performance through use. In subsequent works, implications of this extension to the TTF model, must, however, be clarified. First, the TTF outcomes of use and user performance are concurrent. It is not recognized that in performing the task, the user is using the technology. It is only recognized that to perform the task, the user must use the technology. Thus TTF impacts use and user performance concurrently and sequentially. This notion is quite under-appreciated. Second, the TTF outcome of use impacts user performance. Use is positioned to mediate between TTF and user performance. It must be therefore acknowledged that use is a multi-purpose construct, in being observed as a TTF outcome, performance determinant, and mediator. In light of the above, the processes through which technology is linked to performance have not been sufficiently understood. Naturally, this linkage must thus be further interrogated.

4.7 The Link between Technology and Performance

Crowston and Treacy (1986) observed that the purpose of ITs is to improve performance. As such, attempts have been made to link IT, user evaluations, utilization, and performance, with the sole purpose of modelling IT impacts on performance. The use of an 'Input-Process-Output' model is one such technique (Crowston and Treacy, 1986). This is the selection of a **specific 'process' theory**, and **'inputs'** and **'outputs'** for the precise investigation of the impacts of ITs (p. 308). This model (Figure 4.13) was first proposed for assessing IT impacts on enterprise-level performance (productivity).

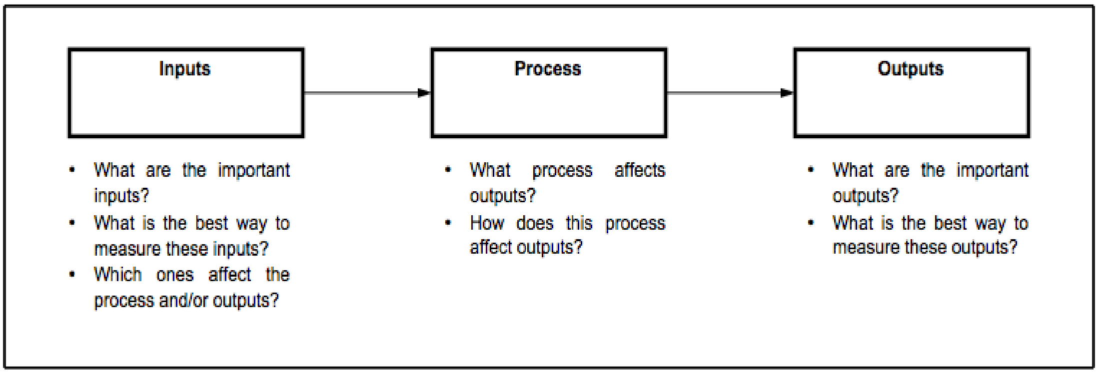

Figure 4.13. Input-Process-Output Model (Crowston and Treacy, 1986, p. 308)

Later, Doll and Torkzadeh (1991) described the modeling of 'end-user computing satisfaction' as a **causal chain with 'forward' and 'backward' linkages**. This is a network of **'cause' and 'effect' relationships** that are considered important for IS research (p. 5). This **causal network, known as the 'System to Value Chain'**, is depicted in Figure 4.14.

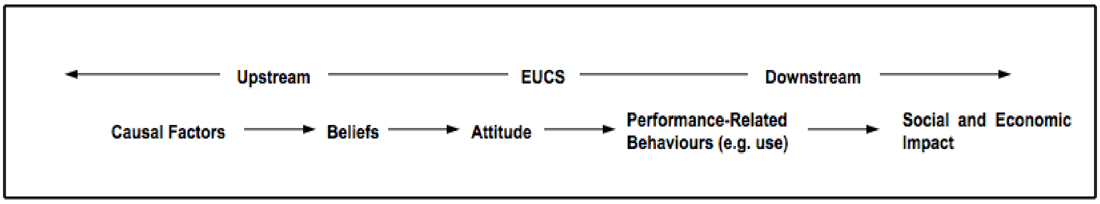

Figure 4.14. System to Value Chain (Doll and Torkzadeh, 1991, p. 6)

In this model, 'end-user computing satisfaction' (EUCS) is both a dependent variable (upstream factors causes of EUCS), and an independent variable (downstream factors are effects of EUCS). As such, causal networks are useful for assessing IT performance impacts. Based on Crowston and Treacy (1986) and Doll and Torkzadeh (1991), Goodhue (1992) presented a linear causal chain linking 'systems' to performance impacts (p. 305). **Input** characteristics such as 'systems', 'user', 'task', and 'organization' were linked to the **output** of 'performance impacts' through the **processes** of 'user evaluation' and 'use of system'. These chain inter-linkages are depicted in Figure 4.15.

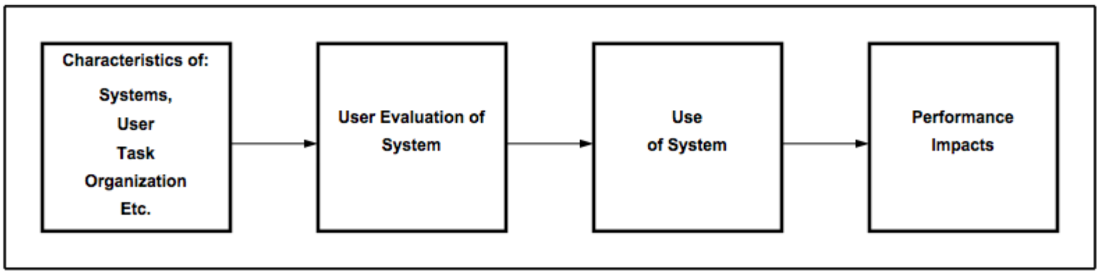

Figure 4.15. A Typical Link between Systems and Performance (Goodhue, 1992, p. 305)

Goodhue (1992) subsequently developed the Systems-to-Performance Chain (Figure 3.15) to link the concepts of systems and IS policies, user tasks, utilization, and performance (p. 304).

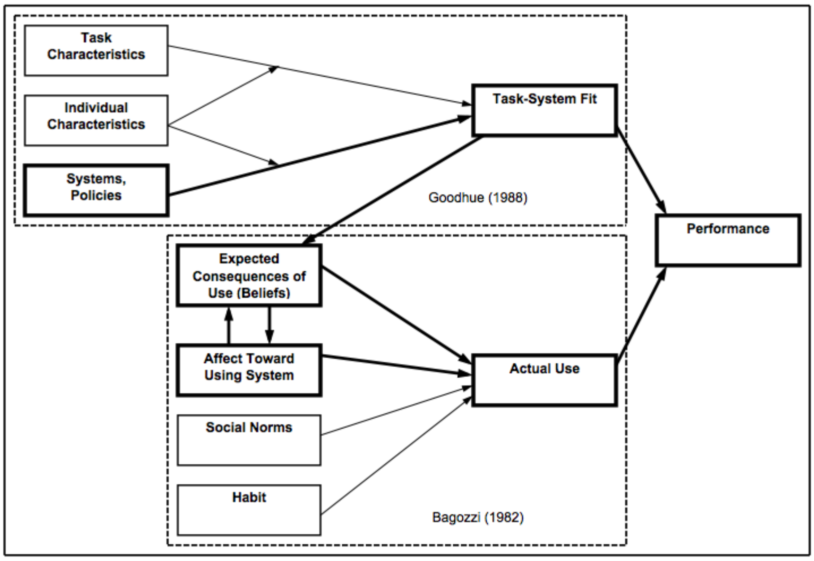

Figure 4.16. The System-to-Performance Chain (Goodhue, 1992, p. 305)

This model (Figure 4.16) links ‘systems, policies’ to ‘performance’ through ‘task-system fit’, ‘expected consequences of use (beliefs)’, ‘affect toward using system’, and ‘actual use’. **‘Task-system fit’ and ‘actual use’ are the core processes through which the system is linked to ‘performance’**. Goodhue (1992) observed that without either a ‘fit’ between the task and system, or its actual use, the system used will not positively impact user ‘performance’ (p. 304). Thus in this particular model, the system impacts performance through a ‘fit’ with the task performed and its use, due to user beliefs of expected use consequences and affect toward using it. The constructs of ‘task-system fit’ and ‘actual-use’ are positioned to directly impact ‘performance’. In addition, ‘social norms’ and ‘habit’ are linked to ‘performance’ through ‘actual use’, and ‘individual characteristics’ are considered to moderate the relationships between ‘task characteristics’ and ‘task-system fit’, and ‘systems, policies’ and ‘task-system fit’. Use is considered a form of behaviour and is considered to have its determinants. Thus the lower portion of the model is underpinned by theories of Attitude and Behaviour (Fishbein and Azjen, 1975; Triandis, 1979). These theories have, notably, together underpinned Bagozzi’s (1982) model of usage, which represents beliefs about consequences of use and affect toward the behaviour of use.

4.8 The Evolution of the Technology-to-Performance Chain (TPC)

Goodhue and Thompson (1995) developed the Technology-to-Performance Chain (TPC), based on its predecessor, the System-to-Performance Chain, and underpinned by both theories of Fit (Goodhue, 1988; Goodhue, 1992) and Attitude and Behaviour (Fishbein and Azjen, 1975; Triandis, 1979), as depicted in Figure 4.17.

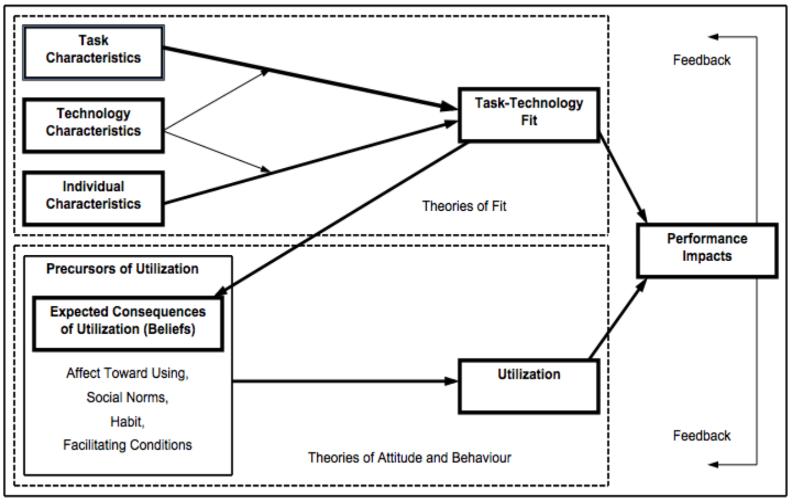

Figure 4.17. Technology-to-Performance Chain (Goodhue and Thompson, 1995, p. 217)

This model links ‘task characteristics’, ‘technology characteristics’, and ‘individual characteristics’ to ‘performance impacts’ through ‘task-technology fit’, ‘expected consequences of use’, and ‘utilization’. **‘Task-technology fit’ and ‘utilization’ are the core processes through which the technology is linked to ‘performance impacts’**. Goodhue and Thompson (1995) observed that TTF-focused models do not sufficiently account for the fact that systems must be used to impact user performance, whereas in utilization-focused models, the ‘fit’ between task and technology was not acknowledged. As such, it was established that the addition of utilization determinants could enrich TTF-focused models, and the inclusion of 'fit' could enhance utilization-focused models. Therefore as per this causal chain, the perspectives of TTF and utilization could together determine performance impacts (p. 216). Thus the characteristics of the task and the individual technology user, impact performance through the 'fit' of the technology to the task performed, together with its utilization, resulting from user beliefs of expected consequences of use. 'Task-technology fit' and 'utilization' are directly linked to 'performance impacts'. In addition, 'affect toward using', 'social norms', 'habit' and 'facilitating conditions' are linked to 'performance impacts' through 'utilization', and 'technology characteristics' are considered to moderate the relationships between 'task characteristics' and 'utilization', and 'individual characteristics' and 'utilization'. Evidently, The TPC is a complex causal model, and has been observed to be difficult to examine in whole. Thus Goodhue and Thompson (1995) proposed a reduced TPC model for testing (p. 219).

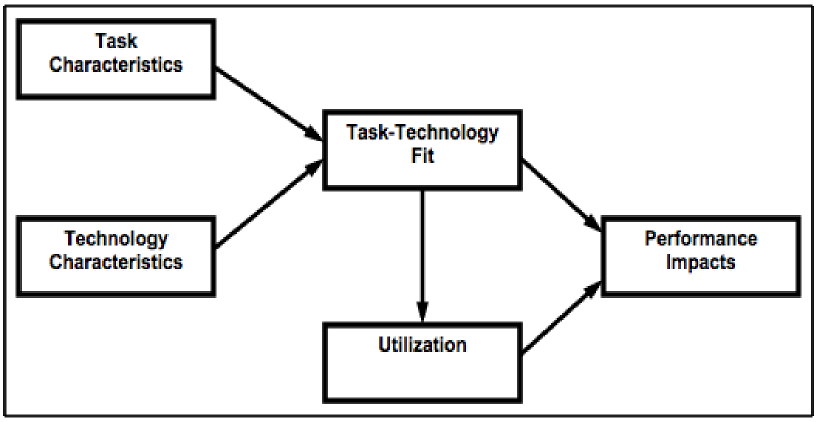

Figure 4.18. Reduced Technology-to-Performance Chain (Goodhue and Thompson, 1995, p. 220)

This model (Figure 4.18) links 'task characteristics', and 'technology characteristics' to 'performance impacts' through 'task-technology fit' and 'utilization'. **'Task-technology fit' is the core process through which the technology is linked to 'performance impacts'**. Thus, task and technology characteristics impact performance through the 'fit' of the technology to the task performed, and its consequent utilization. Notably, utilization is positioned as both a primary and intermediary outcome of 'task-technology fit'. This is consistent with the stated goal of Goodhue and Thompson (1995), which was to examine core TPC components from task and technology, to performance, but with 'particular emphasis on the role of 'task-technology fit' (p. 219). Since determinants of utilization are not depicted in the model, Attitude and Behaviour theories are not applied to account for impacts on utilization. Thus ‘utilization’ is positioned as a consequence of TTF. However, because of the link between ‘utilization’ and ‘performance’, the model is itself an extension of the TTF (Fit-Focus) model (Figure 4.5). Therefore the model is in fact a TPC underpinned by the theory of TTF. In subsequent work, Goodhue (1997) developed a TPC to link the constructs of ‘task characteristics’, ‘technology characteristics’, ‘task-technology fit’, ‘facilitating conditions’, ‘utilization’, and ‘performance impacts’ (p. 450), as depicted in Figure 4.19.

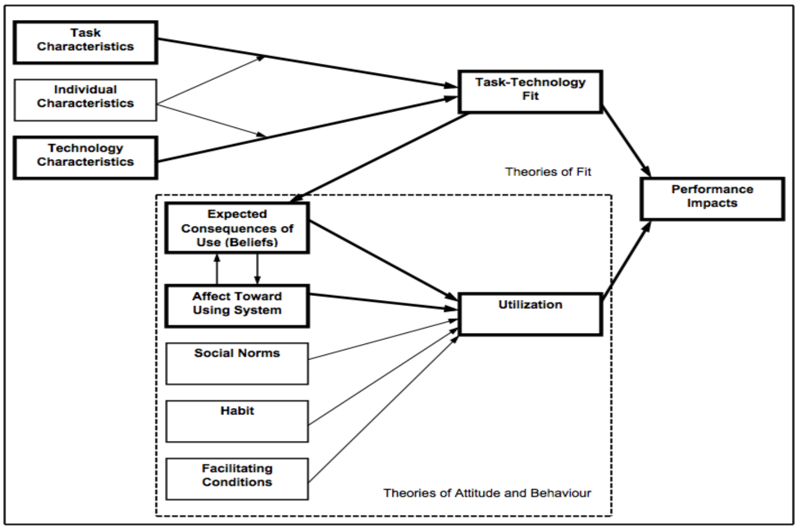

Figure 4.19. Technology-to-Performance Chain (Goodhue, 1997, p. 450)

This model is supposed to link ‘task characteristics’ and ‘technology characteristics’ to ‘performance impacts’ through ‘expected consequences of use’, ‘affect toward using system’, ‘facilitating conditions’ and ‘utilization’. The supposed link between ‘task-technology fit’ and the ‘utilization’ determinant of ‘facilitating conditions’ does not, however, appear to have been expounded. In the original study conducted by Goodhue (1997), ‘facilitating conditions’ was highlighted in the TPC presented, despite no direct apparent linkage between TTF and ‘facilitating conditions’. There appears to be a direct linkage between TTF and ‘expected consequences of use’, to which ‘affect toward using system’ is connected. Goodhue (1997) posited that ‘utilization’ intervenes between ‘technology characteristics’ and individual performance (p. 450). This linkage was, however, unclear. **‘Task-technology fit’ and ‘utilization’ remain as the core processes through which the technology is linked to ‘performance’**. Goodhue (1997) observed that without either a ‘fit’ between the task and technology or its utilization, the system utilized will not enhance ‘performance’ (p. 304). ‘Task-technology fit’ and ‘utilization’ are positioned to directly affect ‘performance impacts’. In addition, ‘social norms’ and ‘habit’ are linked to ‘performance’ through ‘actual use’, and ‘individual characteristics’ are considered to moderate the relationships between ‘task characteristics’ and ‘technology characteristics’, and ‘task-technology fit’. In subsequent work, Goodhue, Littlefield and Straub (1997) developed a more-focused TPC to link the constructs of ‘task characteristics’, ‘technology characteristics’, ‘task-technology fit’, ‘utilization’, ‘performance impacts’, and ‘feedback’ (p. 455) as depicted in Figure 4.20.

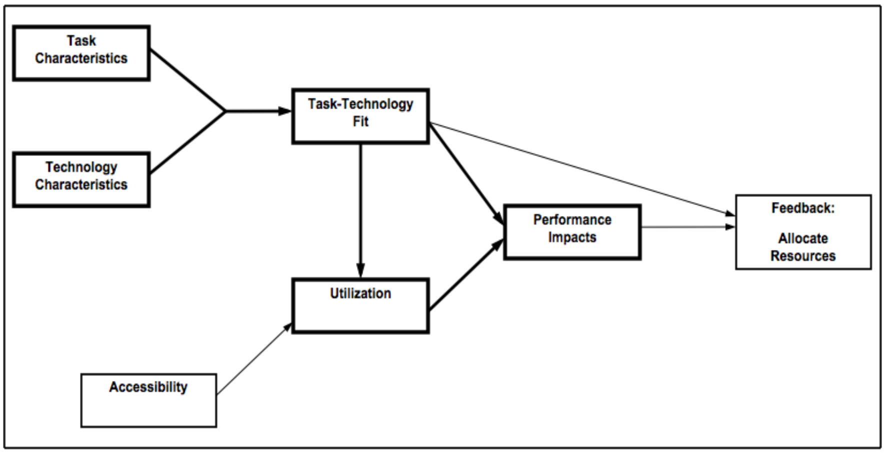

Figure 4.20. Technology-to-Performance Chain (Goodhue, Littlefield and Straub, 1997, p. 455)

This model links ‘task-technology fit’ to ‘performance impacts’ through ‘utilization’, and can essentially be viewed as a TPC underpinned by TTF (Figure 4.18), but with extensions. First, ‘accessibility’ is linked to ‘performance impacts’ through ‘utilization’. As such, utilization is positioned to mediate between ‘accessibility’ and ‘performance impacts’. Second, ‘task-technology fit’ is linked to ‘feedback’ through ‘performance impacts’. As such, ‘performance impacts’ are positioned to mediate between ‘utilization’ and ‘feedback’, and between ‘task-technology fit’ and ‘feedback’. Third, ‘task-technology fit’ is directly linked to ‘feedback’. Thus, the ‘fit’ of the technology to the task, influences subsequent feedback through performance, which it influences directly and through utilization, itself determined by accessibility. Notably, task and technology characteristics are not independently linked to ‘task-technology fit’, but instead combine to form the ‘fit’ construct. **‘Task-technology fit’ and ‘utilization’ remain as the core processes through which the technology is linked to ‘performance impacts’**. Goodhue et al. (1997) observed that the TPC was useful for assessing the validity of the Fit-Focus model and technology performance impacts, with the TTF model as its base. In addition, it was observed that in relation to ‘TTF-Focus’ and ‘Utilization-Focus’ models, a TPC could be reduced and modified to be more specific to a particular context (p. 454). In later work, Staples and Seddon (2004) developed a TPC (Figure 4.21) to link ‘task-technology fit’, a set of ‘precursors of utilization’, ‘utilization’, and ‘performance impacts’ (p. 20).

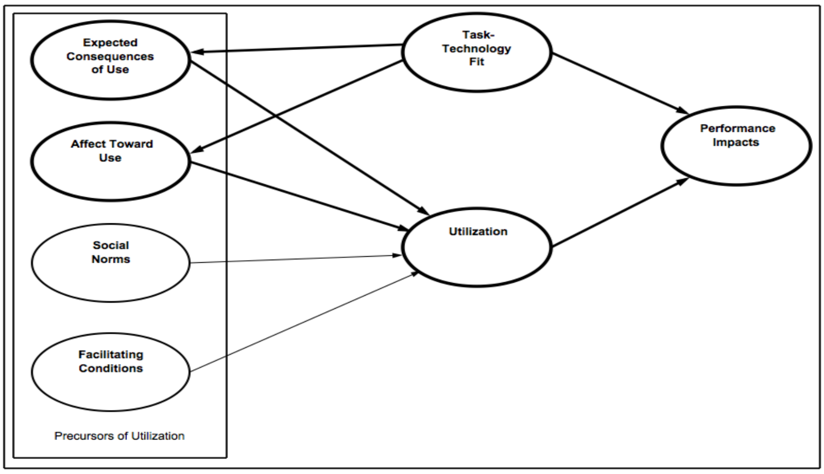

Figure 4.21. Technology-to-Performance Chain (Staples and Seddon, 2004, p. 20)

This model links ‘task-technology fit’ to ‘performance impacts’ through ‘expected consequences of use’, ‘affect toward use’, and ‘utilization’. In addition, ‘task-technology fit’ is directly linked to ‘performance impacts’. The precursors of ‘expected consequences of use’, ‘affect toward use’, ‘social norms’, and ‘facilitating conditions’, are linked to ‘performance impacts’ through ‘utilization’, which is positioned as mediating. Thus, the ‘fit’ of the technology to the task influences performance directly and through expected usage consequences, a user’s affect toward using it, and its eventual utilization, which is also determined by social norms and facilitating conditions. ‘Task-technology fit’ is uni-dimensional, subsuming task and technology characteristics, and representing the user’s evaluation of a ‘fit’ between these characteristics. **‘Task-technology fit’, ‘expected consequences of use’, ‘affect toward use’, and ‘utilization’, are the core processes through which the technology is linked to ‘performance impacts’**. Staples and Seddon (2004) observed that a better ‘fit’ between the task and technology would influence positive expected consequences of use and a higher affect toward using it (p. 21). Notably, the link between ‘task-technology fit’ and ‘utilization’ is absent from their model. Evidently, there are various ways in which technology can be theorized to impact performance, such that multiple TPC models can be developed and examined in various contexts. In TTF-related research, variations based on the above-described TPCs have been proposed. The TPCs[33] that have been conceptualized in various TTF studies are summarized in Table 4.8.

Table 4.8. Technology-to-Performance Chain (TPC) Models

Source	Constructs	Core Process(es)	Key Linkage(s)
D'Ambra and Wilson (2004)	• Task Char • Un Reduct • Tech Char • Indiv Char • Task-Tech Fit • Soc Norm • Cont Fact • Util • Perf Imp	• Task-Tech Fit • Util	• Task → **Task-Tech Fit** → Perf Imp • Tech Char → **Task-Tech Fit** → Perf Imp • Indiv Char → **Task-Tech Fit** → Perf Impacts • Task → **Task-Tech Fit** → **Util** → Perf Imp • Tech Char → **Task-Tech Fit** → **Util** → Perf Imp • Indiv Char → **Task-Tech Fit** → **Util** → Perf Imp
D'Ambra and Wilson (2004b)	• Task • Tech Char • Indiv Char • Task-Tech Fit • Soc Norm • Util • Perf Imp	• Task-Tech Fit • Util	• Task → **Task-Tech Fit** → Perf Imp • Tech Char → **Task-Tech Fit** → Perf Imp • Indiv Char → **Task-Tech Fit** → Perf Imp • Task → **Task-Tech Fit** → **Util** → Perf Imp • Tech Char → **Task-Tech Fit** → **Util** → Perf Imp • Indiv Char → **Task-Tech Fit** → **Util** → Perf Imp
McGill and Klobas (2009)	• Task-Tech Fit • Exp Con Use • Att Use • Soc Norm • Facil Con • Util • Perf Imp	• Task-Tech Fit • Exp Con Use • Att Use • Util	• Task-Tech Fit → Exp Con Use → Att Use → **Utilization** → Perf Imp
McGill, Klobas and Renzi (2011)	• Task-Tech Fit • Soc Norm • Facil Con • Util • Perf Imp	• Util	• Task-Tech Fit → **Utilization** → Perf Imp
D'Ambra, Wilson, and Akter (2013)	• Task • Tech Char • Indiv Char • Task-Tech Fit • Use • Perf	• Task-Tech Fit	• Task → **Task-Tech Fit** → Perf Imp • Tech Char → **Task-Tech Fit** → Perf Imp • Indiv Char → **Task-Tech Fit** → Perf Imp • Task → **Task-Tech Fit** → Use → Perf Imp • Tech Char → **Task-Tech Fit** → Use → Perf Imp • Indiv Char → **Task-Tech Fit** → Use → Perf Imp

Key: Task Char = Task Characteristics, Tech Char = Technology Characteristics, Task-Tech Fit = Task-Technology Fit, Indiv Char = Individual Characteristics, Util/Use = Utilization/Use, Perf/Perf Imp = Performance/Performance Impacts, Exp Con Use = Expected Consequences of Use, Soc Norm = Social Norms, Att Use = Attitude Towards Use, Facil Con = Facilitating Conditions, Cont Fact = Control Factors

[33] Core (key) TPC process linkages are specified (in **boldface**) in Table 4.8. Additional constructs are underlined. The inclusion of these constructs in the TPC necessitates additional linkages, considered as model extensions. These are not specified in the table, as the focus is on the core processes that constitute a TPC i.e. a TPC can function without extensions as long as its core process linkages are specified.

It is evident from the models reviewed in Section 4.7 that there are some notable shortcomings in previous TPC research. These shortcomings have implications for the modeling of TPCs.

4.9 Shortcomings in Technology-to-Performance Chain (TPC) Research

Despite the demonstrated importance of TPCs in TTF research, there have been apparent shortcomings in prior TPC models, particularly those underpinned by TTF theory. First, the conceptual differences between a TTF model and TPC have often been misunderstood. In linking use to user performance, it is apparent that the Fit-Focus TTF model (Figure 4.5) is transformed into a TPC. As such, the TPC is a causal model underpinned by TTF as a theory. This represents an observable difference between TTF and TPC models. Second, the theoretical underpinnings of TPCs are not specified as 'process-influenced'. It is thus important that the theory underpinning a TPC must be determined by a particular mechanism or process through which the technology is expected to impact use and user performance. If, as is intended in the present study, this process is the TTF construct, then it follows that the TPC must be underpinned by the theory of TTF. As such TPCs must be theory driven, and as such TPC theory must be process-specific. Third, the nature of chain construct linkages and their sequencing in TPCs is not often explicated. To understand a TPC process, the path from technology to performance must be completely discernible. Thus the links between TPC constructs and their order of precedence must be clearly described. As such, these constructs and inter-linkages must be annotated. Fourth, the difference between TPC constructs and model extensions is not often qualified. This is characteristic of additional determinants such as precursors of use. In some instances, precursors of use are considered core TPC constructs. However, in most cases, it is not clear whether these are in fact TPC extensions, a distinction that cannot be ignored. If the TPC is TTF-determined, then it appears that logically, precursors of use can only be model extensions, not core chain constructs. This is partly because use is treated as an outcome of the core TPC construct, 'TTF', so that any other determinants of use are considered a posteriori. Consequently, supplementary theory can be used to underpin these TPC extension constructs.

In light of the above, the following implications for the conceptualization of a TPC are identified:

1. It must be recognized that a TPC can be considered an extended TTF model.
2. TPCs must be theorized based on their underlying core processes or mechanisms.
3. The causal linkages between TPC constructs must be verbalized and/or annotated.
4. The inclusion of other determinants of use should be specified as an extension of the TPC.

4.10 Chapter Conclusion

The purpose of this chapter was to discuss Task-Technology Fit (TTF) as the theoretical underpinning of the present study. First, the origin of TTF theory was discussed. Second, the evolution of TTF models developed in prior works was discussed. Third, shortcomings in TTF research were discussed and subsequent implications derived. It is evident that the task and technology must be distinguished from task and technology characteristics, and that the ‘fit’ between these characteristics must be clearly specified. In specifying such a relationship, multiple perspectives of ‘fit’ must be adopted in order to evaluate the distinct effects of TTF on the outcomes of use and user performance. In addition, use can be linked to user performance, and a set of precursors. Consequently, for the present study, the theory of TTF is selected to underpin a Technology-to-Performance Chain (TPC). This TPC is a causal model to link the technology to user performance through a ‘fit’ with the task. In this model, user performance is concurrent with use. However, user performance can also be subsequent to use, and this is recognized. In addition, a set of precursors as additional determinants of use, is considered. As such, a conceptual model linking technology to performance, that is specific to an mHealth setting and CHW task performers as mHealth tool technology users, will be developed in Chapter 5.

5 Conceptual Technology-Performance Chain (TPC) Model Development

5.1 Introduction

In Chapter 4, the theoretical underpinnings of Task-Technology Fit (TTF) and the Technology-to-Performance Chain (TPC) model (Goodhue, 1992; Dishaw, 1994; Goodhue; 1994; Goodhue, 1995; Goodhue and Thompson, 1995) were outlined and discussed. The purpose of this chapter is to develop a TPC conceptual model underpinned by the theory of TTF as postulated in Chapter 4 that links the constructs of 'fit', use, user performance, and a set of precursors as determinants of use. As per the theoretical underpinning of TTF[34], the TTF construct consists of (1) Task Characteristics, (2) Technology Characteristics, and (3) the 'Fit' between Task and Technology Characteristics. These components of the construct of TTF are conceptualized in Section 5.2.

5.2 Task-Technology Fit (TTF)

5.2.1 Task Characteristics

With the embedding of Information Technologies (ITs) into work practices, TTF researchers have begun to examine the task construct and more specifically, task characteristics in the context of technology usage. These task characteristics may result in tool or system users depending more on certain aspects of the technology used to perform the task (Goodhue, 1992). Task characteristics have been considered to be reflective of needs (Nance, 1992), requirements (Goodhue, 1986), or activity demands (Dishaw and Strong, 1998b). For example, in their study on organizational IT usage, Goodhue and Thompson (1995) evaluated transportation enterprise and insurance task characteristics through the dimensions of non-routineness and interdependence. In a software maintenance study, Dishaw and Strong (1998b) evaluated task characteristics such as the user activities of planning, knowledge building, diagnosis, modification, co-operation, and control. Elsewhere, in a study on consulting using Knowledge Management (KM) - portals, Teo and Men (2008) evaluated task characteristics such as knowledge tacitness

[34] Please refer Chapter 4 for a discussion of theoretical underpinnings.

and interdependence. These and various other task characteristics specified in past TTF research are captured in Table 5.1.

Table 5.1. Task Characteristics Task-Technology Fit (TTF) Research			
Construct	Dimension(s)	Context	Source
Task Characteristics	• Non-Routineness • Interdependence	Technology Use in Organizations	Goodhue and Thompson (1995)
Task Activities	• Planning • Knowledge Building • Diagnosis • Modification • Cooperation • Control	Software Engineering Tool Use in Organizations	Dishaw and Strong (1998b)
Task Characteristics	• Accessing Data Files • Quantitative Analysis • Administrative Data • Organizing Documents • Literature Searching	Use of Technologies in an Information Centre	Goodhue et al (1997)
Task Characteristics	• Knowledge Tacitness • Task Interdependence	Use of Knowledge Management Technologies in Consulting Firms	Teo and Men (2008)
Task Characteristics	• Difficult or Non-Routine Tasks • Interdependence	Use of Technologies in Organizations	Goodhue (1995)
Task Characteristics	• Dependence Tasks • Interdependence Tasks • Independent Tasks	Use of Mobile Technologies for Healthcare.	Hsiao and Chen (2012)
Task Characteristics	• Location Sensitiveness vs. Insensitiveness	Use of Mobile Locatable Information Systems	Junglas et al (2008)
Mobile Task Characteristics	• Mobility • Location Dependency • Time Criticality	Use of Mobile Work Technologies	Yuan et al (2010)
Task Characteristics	• Routineness • Interdependence • Spatial Mobility	Use of mHealth Technologies	Tariq and Akter (2011)
Task Difficulty	• Non-Routineness • Interdependence • Time Criticality	Use of Mobile Technologies for Business	Gebauer and Tang (2007)
Task Characteristics	• Non-Routineness • Interdependence • Time Criticality	Use of Mobile Technologies for Managerial Processes	Gebauer et al (2010)

For studies conducted in more formal settings, characteristics such as task difficulty or non-routineness, and interdependence, have typically been evaluated (Goodhue, 1995; Goodhue and Thompson, 1995). However, in some of these studies, actual 'behaviour description' tasks (McCormick 1965; Dunnette, 1966) such as the activities of organizing documents and accessing data files have also been assessed (Goodhue et al., 1997). In studies on user mobility, researchers have evaluated task characteristics such as location sensitiveness, location dependency, spatial mobility, and time criticality (Gebauer and

Tang, 2007; Zheng, 2007; Gebauer, 2008; Gebauer and Tang, 2007; Gebauer et al., 2008; Junglas et al., 2008; Yuan et al., 2010). Some more generic task characterizations such as dependence and interdependence have also been used in contexts that range from consulting (Teo and Men, 2008) to the use of mHealth systems (Tariq and Akter, 2011). Drawing on the above, characteristics most relevant to the tasks performed[35] by CHWs are defined next.

5.2.2 Community Health Worker (CHW) Task Characteristics

In this chapter, the tasks performed by CHWs are described as monitoring, promotion, and referral. Four CHW task characteristics are specified as relevant to their critical job demands. CHWs are required to deliver patient care timeously, co-operate with co-workers, manoeuvre from one location to another, and access information at the point-of-service (Balasubramanian et al., 2002; Junglas and Watson, 2003; Ballard and Siebold, 2004; Gebauer, Shaw and Gribbins, 2005; Junglas et al., 2008; Lin and Huang, 2008; Gebauer, Shaw and Gribbins, 2010; Yuan et al., 2010). These behavioural demands translate into the task characteristics of time criticality, interdependence, mobility, and information dependency.

First, *time criticality* is the need of the task performer to urgently perform the task (Gebauer and Tang, 2007). This characteristic has been adapted in prior works to evaluate tasks performed using mobile technologies. For example, Siao, Lim and Shen (2001), Yuan and Zhang (2003), and Liang and Wei (2004), observed that task performers could be required to support emergency services. This underscores the time critical nature of the tasks being performed. Time criticality may be a greater characteristic for CHW tasks such as patient referral to clinics for emergency treatment (Liu et al., 2011), but perhaps less so for those such as the promotion of immunization (Haines et al., 2007).

Second, *interdependence* is the need of the task performer to co-operate with others in preforming the task (Gebauer et al., 2010). In certain workplace settings such as Research and Development (R & D) laboratories for co-ordinated software projects (Andres and Zmud, 2002), task interdependence may be greater than in others such as goal-oriented supervised information processing within dissimilar work units (Tushman, 1979). In the

[35] Please refer Section 4.6.1 of Chapter 4.

health care setting, the need for care-givers such as nurses to co-operate in the sharing of medical data with one another to solve pending medical problems, increases the task interdependence of their work (Hsiao and Chen, 2012). For CHWs, task interdependence is high if there is a need to co-ordinate through information-sharing, such as when co-operating with local community health supervisors during real-time disease surveillance household exercises (Braun et al., 2013).

Third, *mobility* is the need of the task performer for manoeuvrability in performing the task (Gebauer et al., 2010). This characteristic is a location-sensitive (geographical) component of the activity of the task performer (Junglas et al., 2008), and has been assessed in various studies on mobile technologies. For example, in their study on mobile work, Yuan, Archer, Connelly, and Zheng (2010) argued that compared to their hospital-based counterparts, home-visiting nurses needed greater support for task mobility. CHW task mobility is high if there is a need to collect health data from patients in remote locations when they routinely visit households to deliver patient care (DeRenzi et al., 2012).

Fourth, *information dependency* is the need of the performer to access data in performing the task at the point-of-service (Yuan et al., 2010). This characteristic is related to the concept of location-dependency, described as the extent to which dynamic location-based information is required to perform a particular task (p. 126). This location-sensitive (information) task component has been assessed in a number of studies on mobile technology adoption. For example, Junglas, Abraham, and Watson (2008) observed that in performing their tasks, mobile workers use data specific to their locations of service. CHW task information dependency is high if there is a need for data on household locations for monitoring when conducting disease surveillance (Earth Institute, 2010).

5.2.3 Technology Characteristics

In the TTF IS domain, technology has often been characterized as system or tool features that represent the applications, infrastructure, or services that support the execution of tasks (Tariq and Akter, 2011). This is irrespective of whether the technology used represents a system or systems, policies, or services (Cane and McCarthy, 2009). TTF researchers have begun to examine the technology construct and more specifically, technology characteristics in the context of supporting task performance. Technologies have been described as system attributes, and tool functions or functional support (Dishaw and Strong, 1998b; Tariq and Akter, 2011; D'Ambra et al., 2013). Technology characteristics are considered to be reflective of support functions (Dishaw and Strong, 2003), functionality (Gebauer, Shaw and Gribbins, 2010), or attributes (D'Ambra and Rice, 2001). A broad range of technology characteristics have been evaluated in past studies. For example, Teo and Men (2008) evaluated the Knowledge Management (KM) - portal technology characteristics of output quality and compatibility (p. 561). Elsewhere, Dishaw and Strong (1998b) evaluated the software maintenance technology characteristics of analysis, representation, transformation, co-operation, and control (p. 110). These and various other technology characteristics specified in past TTF research are captured in Table 5.2.

Table 5.2. Technology Characteristics in Task-Technology Fit (TTF) Research

Construct	Dimension(s)	Context	Source
Technology Characteristics	• Access	Web Usage for Travel	D'Ambra and Wilson (2004a)
Tool Functionality	• Analysis • Representation • Transformation • Cooperation • Control	Software Engineering Tool Use in Organizations	Dishaw and Strong (1998b)
Technology Characteristics	• Output Quality • Compatibility	Use of Knowledge Management Technologies in Consulting Firms	Teo and Men (2008)
m-NIS Characteristics	• Degree of Integration • Service Support	Use of Mobile Technologies for Healthcare.	Hsiao and Chen (2012)
Technology Characteristics	• Combined Locatability and Mobility	Use of Mobile Locatable Information Systems	Junglas et al (2008)
Functions of Mobile Work Support	• Mobile Notification • Location Tracking • Navigation • Real Time Mobile Job Dispatching	Use of Mobile Work Technologies	Yuan et al (2010)
Mobile IT	• User Interface • Adaptability	Use of Mobile Technologies for Managerial Processes	Gebauer et al (2010)

In prior TTF studies on user mobility, researchers have evaluated technology characteristics such as location tracking, navigation, notification, real-time job dispatching, user interface, and adaptability (Junglas et al., 2008; Gebauer et al., 2010; Yuan et al., 2010). In TTF research, mobile technology characteristics have been described as work support functions (Zheng, 2007, p. 17; Yuan et al., 2010, p. 126; Hsiao and Chen, 2012, p. 266). For instance, Liang and Wei (2004) characterized mobile technology into the categories of time-critical services, location-aware and location-sensitive services, identity-enacted services, ubiquitous communications and content delivery services, business process streamlining, and mobile offices. Elsewhere, Balasubramanian, Peterson and Jarvenpaa (2002) categorized mobile technology along three dimensions described as the extent to which the tool or system used is (1) location sensitive, (2) time-critical, and (3) controlled by the information receiver or provider. Per TTF theory, technology functions must support user needs. Moreover, the technology will only be used if tool or system functions rendered support user activities (Vessey and Galleta, 1991; Goodhue, 1998; Dishaw and Strong, 1998b; Dishaw and Strong, 1999; Hollingsworth, 2015). Of note, functional support can be understood in terms of functional and non-functional requirements. Functional requirements are described as ‘specific behaviours’ of a system that are inherent in the functions that ‘it can perform’. These requirements determine what the system ‘can do’ and the extent to which user tasks can be supported. Non-functional requirements are functions that relate to the ‘operation of the system’. These requirements determine what the system ‘should be’ (Gebauer, Tang and Baimai, 2007).

In the present study, the focus is more on mHealth technology design than hardware specifications. However, mHealth tools can be understood to incorporate both functional and non-functional characteristics. In line with TTF theory, the design of technology for task requirements is important to the technology user, who will have expectations of the functional support of the tool for their needs, and not necessarily its underlying architecture. In essence, the present study is restrictive to features designed to support CHW needs. In Section 5.2.3, four mHealth technology user needs are identified as relevant to the critical behavioural job demands of CHWs. These were the task characteristics of time criticality, interdependence, mobility, and information dependency. Therefore functional support of the mHealth tool for CHW tasks is needed. Drawing on the above, characteristics most relevant to the mHealth technology used[36] by CHWs are defined next.

[36] Please refer Section 4.6.2 of Chapter 4.

5.2.4 Mobile-Health (mHealth) Technology Characteristics

In this chapter, the technology used by the CHW as the user, is described as an mHealth tool. Four mHealth tool technology characteristics are specified as relevant properties to be utilized by CHWs. These properties must be designed as mobile support functions for critical CHW task needs. CHWs need mHealth tools with supporting functions for emergency (time-critical) services, mobility from one location to another, data integration and information sharing, and access to data at the point-of-service (Balasubramanian et al., 2002; Liang and Wei, 2004; Junglas and Watson, 2006; Hsiao and Chen, 2012). These properties of the mHealth tool translate into the technology characteristics of time criticality support, interdependence support, mobility support, and information dependency support.

First, *time criticality support* is the function designed for the user need of the task performer to respond urgently (Gebauer and Shaw, 2004). This support function has been evaluated in prior works on mobile technology use for task performance. For example, the time critical function of mobile notification is used to remind the performer when urgent tasks need to be performed immediately or during emergencies (Yuan et al., 2010). If the time criticality of CHW tasks is high, then mHealth tool notification e.g. event-trigger SMS messages, is critical i.e. during emergencies. This would prompt CHWs to respond quickly and if need be, refer patients to hospitals or clinics for further care or specialized treatment (Liu et al., 2011).

Second, *interdependence support* is the function designed for the user need of the task performer to co-operate with others in preforming the task (Dishaw and Strong, 1998b). This support function, evaluated as co-ordination functionality in the context of software maintenance, can be applied to study mobile technology use for task performance. For example, integrated common systems are used to support collaborative information sharing between task performers for decision-making (Hsiao and Chen, 2012). If CHW task interdependence is high, then mHealth tool interpersonal functionality for communication e.g. the interactive transmission of voice and text, is critical i.e. for integration of data, processing, and sharing. This information would support CHWs in sharing household health data in co-ordination with community supervisors when real-time disease surveillance is conducted (Braun et al., 2013).

Third, *mobility support* is the function designed for the user need for location manoeuvrability of the task performer (Yuan et al., 2010). This support function has been evaluated in research on mobile work. For example, location-tracking is used to identify and locate task performers (Zhao, Shin and Reich, 2002). If CHW task mobility is high, then mHealth tool location-tracking service e.g. GPS-enabled navigation, is critical i.e. to map a target destination, relative to the movement of the user. This would support CHWs in moving to remote locations to collect data from patients during household visits (DeRenzi et al., 2012).

Fourth, *information dependency support* is the function designed for the user need of the task performer to access data at the point-of-service (Junglas et al., 2008). This support function has been evaluated as location dependency in previous research on user mobility. For example, mobile locatability is a function used to provide task performers with location-specific information (Yuan et al., 2010). If CHW task information dependency is high, then mHealth tool location-aware service e.g. localized data in real-time, is critical i.e. for access to data on the user's location relative to others, and objects such as supplies or equipment. This would support CHW household surveillance initiatives (Earth Institute, 2010).

CHWs need support from an mHealth tool for (1) timely healthcare delivery e.g. when they need to refer patients to clinics or hospitals for emergency care, (2) co-operation as co-workers e.g. when they need to share information in co-ordination with community health supervisors, (3) manoeuvrability e.g. when they need to visit households to deliver care, and (4) real-time access to information at the point of patient care e.g. when they need household data 'on-location' during monitoring for surveillance. The technology, therefore, must represent functional support for time criticality, interdependence, mobility, and information dependency needs. According to TTF theory for optimal technology use and user performance, characteristics of the tool used must 'fit' characteristics of the work tasks being performed (Dishaw, 1994; Goodhue and Thompson, 1995; Kilmon, Fagan, Pandey and Belt, 2008). This concept of a 'fit' between the task and technology is conceptualized next.

5.2.5 The Fit between the Task and Technology

The 'fit' between the technology used by the task performer, and the task performed by the technology user, is the third component of Task-Technology Fit (TTF). The 'fit' between task and technology is conceptualized by drawing on the work of Venkatraman (1989), who classified six perspectives of 'fit' (p. 438). Four of these 'fit' perspectives are used for the purposes of the present study. The first perspective of 'fit', Fit as Matching, refers to the pairing of two related variables (Venkatraman, 1989, p. 430). It has been used to inform 'fit' concepts in strategy research (Bergeron, Raymond and Rivard, 2001), and adapted for IS research. For example, Dishaw and Strong (1998b) expressed the relationship between user activities and tool functionality using a TTF matrix to illustrate their matching pairs (p. 110), and postulated that 'fit' as the matching of certain task (user) activities and technology (tool) support functions, occurs as shown on the shaded diagonal depicted in Figure 5.1. They then modelled its intended effect on tool use as depicted in Figure 5.2.

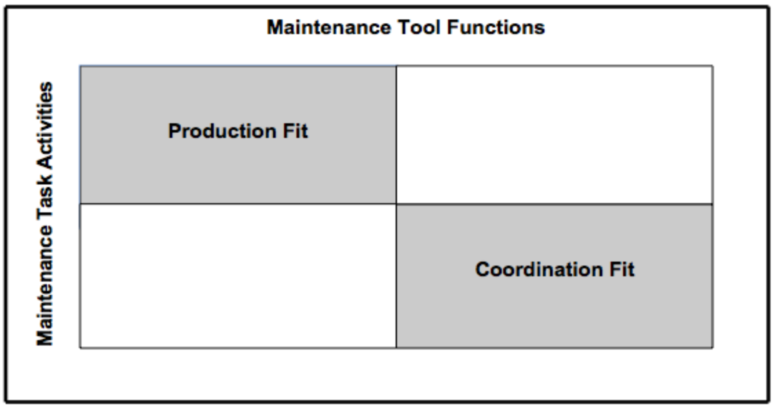

Figure 5.1. Task-Technology Fit (TTF) Matrix (Dishaw and Strong, 1998b, p. 110)

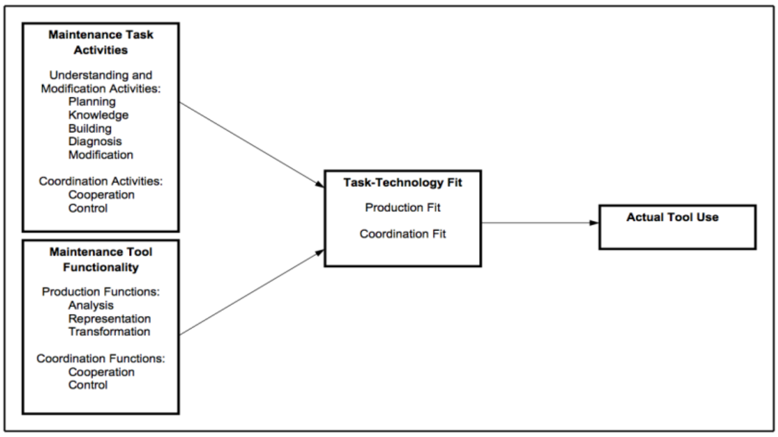

Figure 5.2. Fit of Tool Functionality to User Activity (Dishaw and Strong, 1998b, p. 109)

Similarly, in the present study, the relationship between the identified mHealth tool support functions and CHW task characteristics can be expressed using a TTF matrix as illustrated in Figure 5.3.

Technology (Tool Function)

Task (User Need)	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality				
Interdependence				
Mobility				
Information Dependency				

Figure 5.3. Task-Technology Fit (TTF) Matrix: Matching

These matching CHW task and mHealth tool characteristics form the shaded diagonal in Figure 5.3. Subsequently, the effects of TTF as Matching on use and user performance can be modelled as illustrated in Figure 5.4.

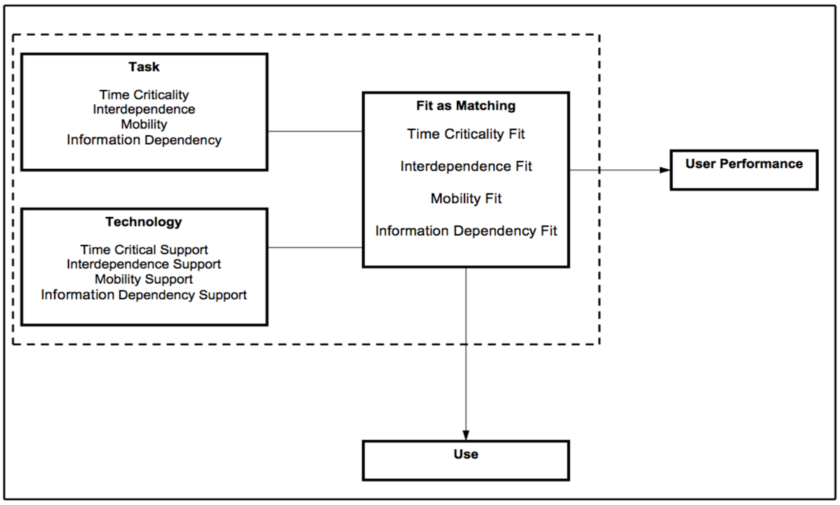

Figure 5.4. Task-Technology Fit (TTF) as Matching Model

The second perspective of 'fit', Fit as Moderation, occurs when the impact of a predictor variable on a criterion variable depends on the level of a third variable, the moderator (Venkatraman, 1989 p. 424). Venkatraman (1989) observed that Moderation could be examined by testing 'fit' as an interaction effect (p. 425). This perspective has been applied in IS research where TTF as Moderation was modelled as the interaction (Figure 5.5) of Knowledge Management (KM) task and technology characteristics (Teo and Men, 2008). Since its effects on a criterion are specified, Fit as Moderation has been classified as a criterion-specific form of 'fit' (Venkatraman, 1989).

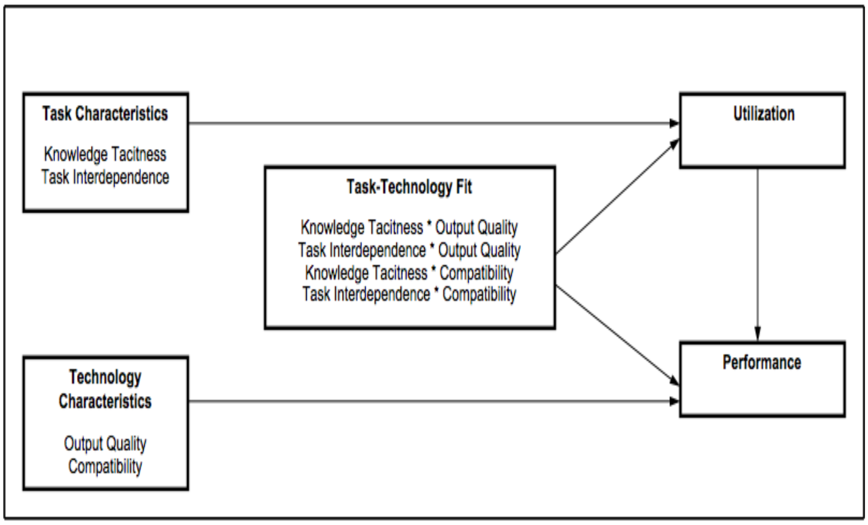

Figure 5.5. Fit of Knowledge Management (KM) Technology to Knowledge Task (Teo and Men, p. 561)

This interaction is calculated as the cross-product of each task with each technology characteristic. In the present study, similar interactions can be conceptualized to include both on-diagonal and off-diagonal cells, expressed using a TTF matrix as illustrated in Figure 5.6.

Technology (Tool Functions)

Task (User Needs)

	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	FIT	FIT	FIT	FIT
Interdependence	FIT	FIT	FIT	FIT
Mobility	FIT	FIT	FIT	FIT
Information Dependency	FIT	FIT	FIT	FIT

Figure 5.6. Task-Technology Fit (TTF) Matrix: Moderation (Interaction)

Based on the approach of Teo and Men (2008), the effects of TTF as Moderation on use and user performance can be modelled as depicted in Figure 5.7.

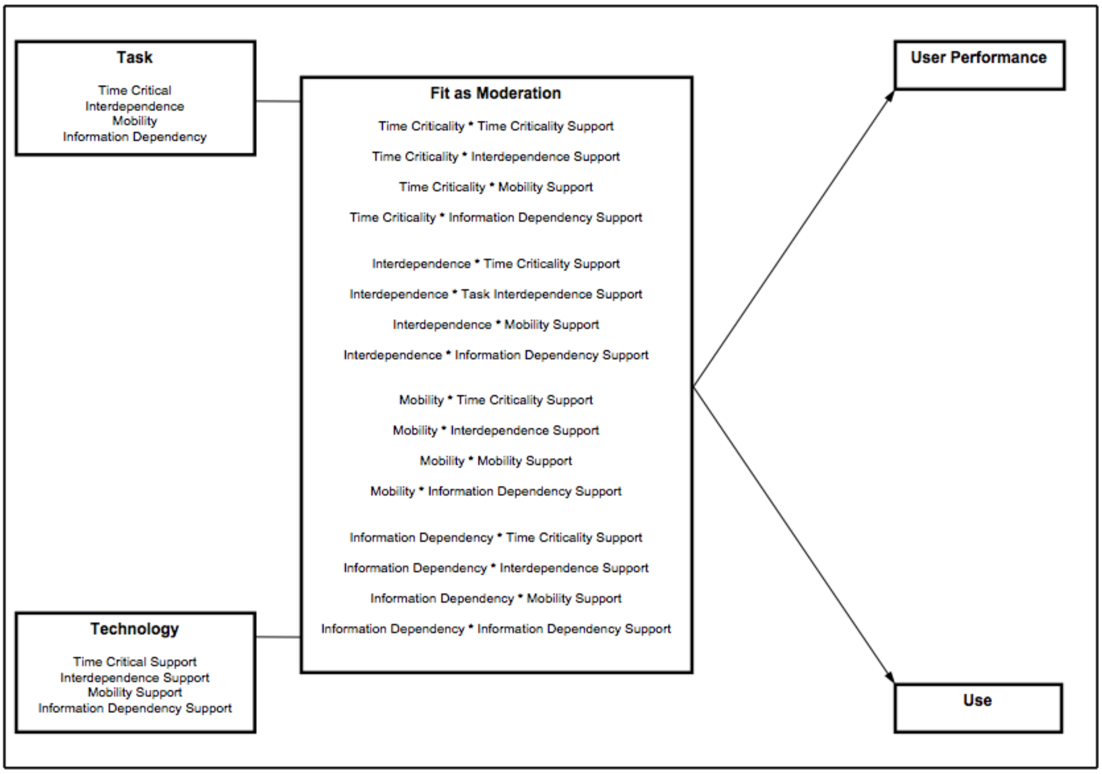

Figure 5.7. Task-Technology Fit (TTF) as Moderation (Interaction) Model

The third perspective of ‘fit’, Fit as Mediation, involves an intervening mechanism, a mediator, positioned between one or more predictor and criterion variables

(Venkatraman, 1989, p. 428). This perspective originated from research on strategic management (Bergeron et al., 2001), and can be used to conceptualize a ‘fit’ between task and technology characteristics. Venkatraman (1989) suggested that this ‘fit’ could be evaluated by testing the intervening, indirect effects of a predictor (or set of predictors) on a consequent variable. This perspective of ‘fit’ is adaptable to TTF research. For example, in their Fit-Focus model (Figure 5.8), which is representative of a traditional TTF model, Goodhue and Thompson (1995) positioned the TTF construct as a user-evaluation between antecedent task and technology characteristics, and consequent utilization and performance impacts (p. 215). Since its effects on a criterion are specified, Fit as Mediation has also been classified as a criterion-specific form of ‘fit’ (Venkatraman, 1989).

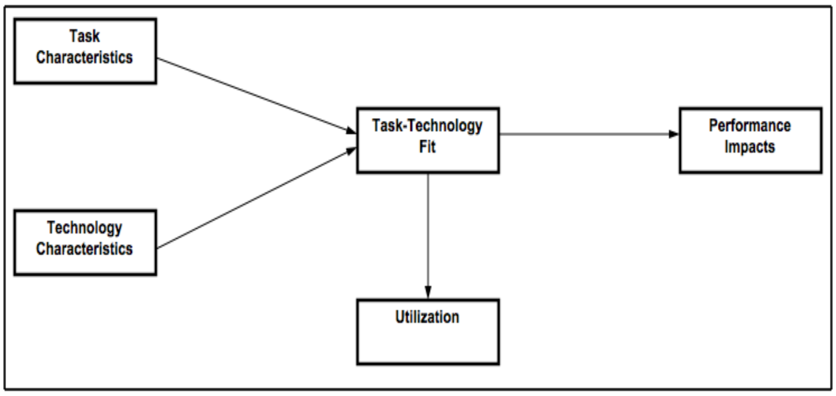

Figure 5.8. Fit-Focus Model (Goodhue and Thompson, 1995, p. 215)

The Goodhue and Thompson (1995) Fit-Focus model is adopted for the present study where the ‘fit’ of mHealth technology characteristics to CHW task characteristics is modelled as a user evaluation. Notably, it appears that in prior works, ‘fit’ as a user evaluation has not typically been described as mediating despite its positioning as an intervening variable between antecedent task and technology characteristics, and consequent use and user performance outcomes, and has neither been classified nor tested as such. This intervening ‘fit’ links these task and technology characteristics to use and user performance, as depicted in Figure 5.9.

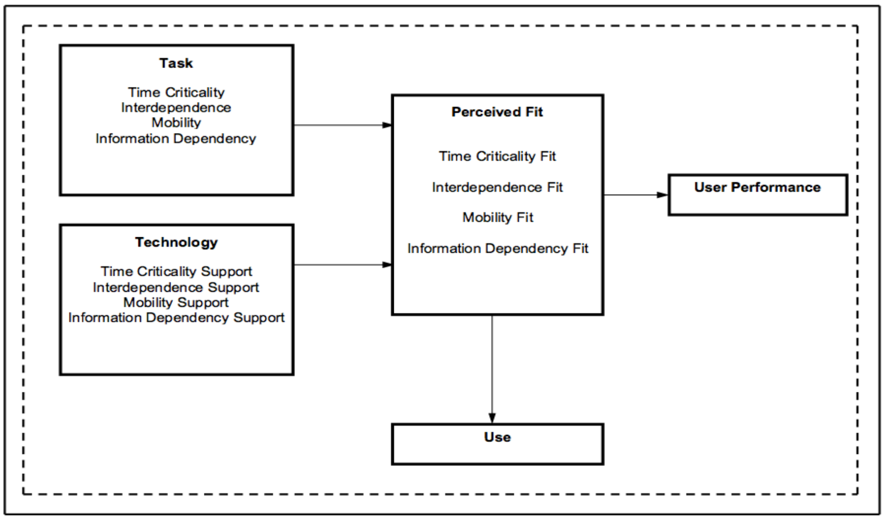

Figure 5.9. Task-Technology Fit (TTF) as Mediation Model

The fourth and final perspective of 'fit' is Fit as Covariation, which is observed as a pattern of internal consistency among a set of underlying and theoretically related variables (Venkatraman, 1989 p. 435). This 'fit' perspective has been used in research on 'fit' in strategic management (Bergeron et al., 2001), and in the IS discipline in research on 'fit' for ERP implementation (Wang, Shih, Jiang and Klein, 2008). However, curiously, it has never been adapted for TTF research. Venkatraman (1989) suggested that 'fit' could be evaluated as a pattern of internally consistent, co-aligned factors, tested for its effects on use and user performance. In a broader IS study, Wang et al's (2008) conceptualization of co-alignment as internal consistency for their study of Enterprise Resource Planning (ERP) success factors, is depicted in Figure 5.10. The co-alignment amongst these six success factors is further depicted as impacting on outcomes such as decision-making and control, and efficiency and profitability. Although this form of 'fit' was originally classified as criterion-free (Venkatraman, 1989), it can be evaluated as criterion-specific since its effects on an outcome or outcomes are specified.

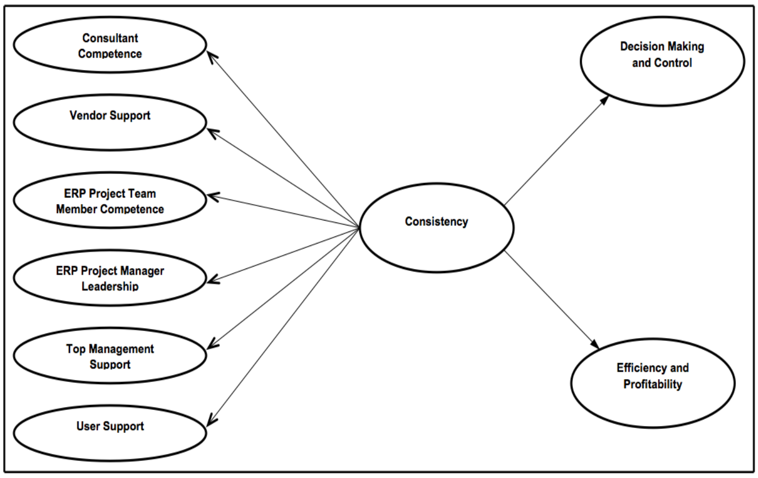

Figure 5.10. The Fit as Covariation (Consistency) of Enterprise Resource Planning (ERP) Factors (Wang et al., 2008, p. 1613)

In the present study, this perspective of 'fit' as a pattern of co-aligned CHW task characteristics and mHealth technology characteristics is depicted[37] in Figure 5.11, with expected consequent effects for use and performance. Specifically, covariation 'fit' is represented as a second-order factor, with first-order task and technology factors as its reflective indicators (Venkatraman, 1990; Segars, Grover and Teng, 1998). This model specification has been described as a reflective first-order, reflective second-order (Type I) model, one in which the second-order construct (TTF) has underlying first-order factors (task and technology characteristics) as reflective dimensions, which themselves are measured using reflective manifest indicators[38] (Jarvis, Mackenzie and Podsakoff, 2003, p. 204).

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[37] For schematic clarity, the reflective indicators of the first-order factors (task and technology characteristics) are not drawn here. These task and technology characteristics are latent constructs, each being a reflective indicator of 'fit' (Jarvis et al., 2003).

[38] Please refer Tables E.1 and E.2 of Appendix E for a detailed description of task and technology characteristics.

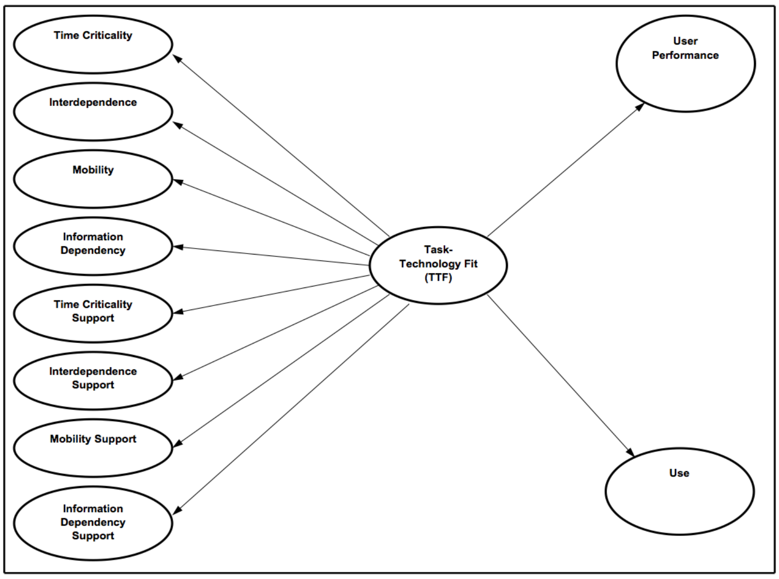

Figure 5.11. Task-Technology Fit (TTF) as Covariation Model

The technology the task performer uses to perform the task is linked through TTF theory to use and user performance. The TTF outcome constructs of use and user performance are discussed in Sections 5.3 and 5.4.

5.3 Use in Task-Technology Fit (TTF) Research

Various dimensions of the concept of technology use have been evaluated in TTF research. For instance, Teo and Men (2008) operationalized use as frequency, intensity and extent of use. Similarly, McGill, Klobas and Renzi (2011) operationalized use as frequency of use and intensity of use. Elsewhere, Dishaw and Strong (1998b) operationalized use as extent of use. One promising use concept in TTF research relates to use as user dependence on the system (Junglas et al., 2009). This is because task characteristics may move users to depend more on certain aspects of a technology that is being used (Goodhue and Thompson, 1995, p. 216). This reflects the extent to which use of the tool is integral to typical task routines (Trice and Treacy, 1986). Goodhue and Thompson (1995) evaluated use as the user's dependence on the system being used (p. 223). For optimal use, the technology used must 'fit' the task performed (Dishaw, 1994). As per the traditional Fit-Focus TTF model (Goodhue and Thompson, 1995), user dependence has been evaluated as a dimension of use consequent to TTF. In their study of Mobile Information Communication Technology (MICT) use by nurses, Junglas, Abraham and Ives (2009) evaluated dependence as the extent to which the user became dependent on the technology in performing the task (p. 645). These and various other use dimensions specified in past TTF research are captured in Table 5.3.

Table 5.3. Use Concepts in Task-Technology Fit (TTF) Research			
Use Construct	Dimension(s)	Context	Source
Tool Utilization	• Extent of Use	Software Maintenance	Dishaw and Strong (1998a, 1998b)
Utilization	• Extent of Technology Use	Use of Software for Operations Management Courses	Dishaw et al (2006)
KMS Usage	• Frequency	Use of Knowledge Management Technologies in Companies	Lin and Huang (2008)
Utilization	• Time Spent Using System	Use of Virtual Learning Environments (VLEs)	McGill and Hobbs (2007)
Utilization	• Frequency of Use • Intensity of Use	Use of Learning Management Systems (LMs)	McGill and Klobas (2009)
Utilization	• Frequency of Use • Intensity of Use	Use of Learning Management Systems (LMs)	McGill, Klobas and Renzi (2011)
Utilization	• Frequency • Intensity • Extent of Use	Use of Knowledge Portals	Teo and Men (2008)
Utilization Impact	• Dependence on the System	Use of Mobile Technologies in a Hospital	Junglas et al (2009)
Usage	• Extent of Use	Technology use among mobile professionals.	Gebauer (2008)
Extent of Use	• Extent of Use	The general use of mobile information systems.	Gebauer and Ginsburg (2009)

Of note, use dimensions have rarely been evaluated in mobile technology and healthcare TTF research. Drawing on the above, a technology use construct is conceptualized for the present study.

5.3.1 Mobile-Health (mHealth) Technology Use

For the efficacious delivery of patient care, the use of mHealth tools by CHWs at the point-of-care can encompasses three technology use dimensions, namely ‘frequency’, ‘intensity’, and ‘dependence’.

First, *frequency* is how many times on average the user uses the technology in task performance (Lee, 1986; Lee, Kozar and Larsen, 2003; Teo and Men, 2008). The repetitive use of ITs has been cited as evidence of enhanced frequency of use of the technology (Hou, 2012).

Second, *intensity* is how much time on average the user spends using the technology in performing tasks (McGill and Hobbs, 2007). In general, the more the user uses the technology in performing tasks, the greater their level of intense tool or system usage. However, in particular contexts, it has been acknowledged that a more advanced or sophisticated IT user may spend less time using the technology than is expected of the average user (Igbaria, Zinatelli, Cragg and Cavaye, 1997).

Third, *dependence* is the extent to which the user has come to rely on using the technology in task performance (Junglas et al., 2009). The integration of ITs into individual work routines has been observed to enhance user dependence as the technology becomes more integral to the tasks being performed (Goodhue and Thompson, 1995).

5.4 User Performance in Task-Technology Fit (TTF) Research

Various dimensions of the concept of user performance have been evaluated in TTF research. For example, in their study of system users, Goodhue and Thompson (1995) evaluated performance impacts as the dimensions of effectiveness and productivity. Perceptual measures have been used because more objective dimensions are deemed incompatible in contexts where technology users perform various tasks (Goodhue and Thompson, 1995). In a study of information centre end-users, Goodhue (1997) contended that performance represents a combination of improved efficiency, effectiveness and quality. Variations of these user performance dimensions have been used in TTF research. In an academic setting, Staples and Seddon (2004) assessed performance impacts as user perceptions of system worth, effectiveness, efficiency, and satisfaction. Similarly, in a study on the use of e-books, D'Ambra, Wilson and Akter (2012) assessed performance as the user perceptions of improved quality, productivity, and effectiveness. Elsewhere, in a knowledge work setting, Teo and Men (2008) evaluated performance as the measure of work operation efficiency, worker effectiveness, and quality. In research on web usage, D'Ambra and Rice (2001) assessed performance as a perceptual construct comprising the dimensions of impact on user ability to accomplish tasks, increased communication with others, improved work quality, better decision making, increased task completion speed, and improved access to information. In their study on Spatial Decision Support Systems (SDSS), Jarupathirun and Zahedi (2003) measured performance as technology satisfaction, quality, and efficiency. These and other user performance concepts in TTF research are captured in Table 5.4.

Table 5.4. User Performance Concepts in Task-Technology Fit (TTF) Research		
Construct	Dimension(s)	Source
Performance Impacts	• Effectiveness • Productivity	Goodhue and Thompson (1995)
Performance	• Efficiency • Effectiveness • Quality	Goodhue (1997)
Performance Impacts	• System Worth • Effectiveness • Efficiency • Satisfaction	Staples and Seddon (2004)
Performance	• Quality • Productivity • Effectiveness	D'Ambra, Wilson and Akter (2012)
Performance	• Efficiency • Productivity • Effectiveness • Quality	Teo and Men (2008)
Performance	• User Ability to Accomplish Tasks • Communication with Others • Work Quality • Decision-Making • Task Completion Speed • Access to Information	D'Ambra and Rice (2001)
Performance	• Decision Satisfaction • Technology Satisfaction • Perceived Decision Quality • Perceived Decision Efficiency	Jarupathirun and Zahedi (2003)
Performance Impact	• Effectiveness • Efficiency • Quality of Care • Decreased Error Rates	Junglas et al (2009)
Nursing Performance	• Nursing Speed • Quality • Efficiency	Goodhue (1997)
Performance	• Quality of Care	Karsh et al (2009)
CHW Performance	• Efficiency • Effectiveness • Quality	Tariq and Akter (2011)
Individual Performance	• Time taken to complete tasks	Junglas et al (2008)
Performance	• Speed • Accuracy • Decision Quality • Effectiveness • Efficiency	Gebauer et al (2005)
Overall System Evaluation	• System Rating • Perceived System Quality • Price Value	Gebauer et al (2007)

Similar user performance dimensions have been evaluated in mobile technology and healthcare research. For example, in a study on the use of Mobile Information Communication Technologies (MICTs) by nurses, Junglas, Abraham, and Ives (2009) evaluated performance comprising effectiveness, efficiency, and quality dimensions of patient care. These dimensions were self-reported measures. Elsewhere, in a study on mobile-Nursing Information Systems (m-NISs), Hsiao and Chen (2012) evaluated performance using the dimensions of speed, quality and efficiency of nursing performance. In other work, Karsh, Holden, Escoto, Alper, Scanlon, Arnold, Skibinski and Brown (2009) evaluated performance as the perceived quality of patient care in hospital settings from the perspective of nurses. In similar work on mHealth technologies in developing countries, Tariq and Akter (2011) described performance as the efficiency, effectiveness, and quality of CHW task completion. Elsewhere, in a study on mobile locatable systems, Junglas, Abraham, and Watson (2008) evaluated individual performance as the time users spent completing their tasks (p. 1051). In other work, in a study on mobile system use, Gebauer, Shaw and Gribbins (2005) measured performance as perceived user speed, accuracy, decision quality, and efficiency. In a related study on mobile user requirements, Gebauer, Tang, and Baimai (2007) assessed performance as a user system rating capturing quality and price value. Drawing on the above, a user performance construct is conceptualized for the present study.

5.4.1 Community Health Worker (CHW) Performance

In prior works, higher performance levels have been defined as the improvement in effectiveness, efficiency and quality (Staples and Seddon, 2004; Bravo, Santana and Rodon, 2015). In the mobile technology and healthcare context, these three dimensions of user performance have been emergent (Junglas et al., 2009).

First, *effectiveness* is the execution of actions or tasks to achieve desired work outcomes or results (Teo and Men, 2008). ITs have been shown to improve the effectiveness of users by enhancing their productive output in executing tasks (Torkzadeh and Doll, 1999).

Second, *efficiency* is the completion of tasks in the least time, and at the lowest cost (Garrity and Sanders, 1998). ITs have been shown to improve the efficiency of users by automating time-consuming tasks, thereby reducing the wastage of resources (Belanger, Collins and Cheney, 2001).

Third, *quality* is the completion of tasks without committing errors (Junglas et al., 2009). ITs have been shown to improve output quality not only by validating the inputs of tool or system users, but also minimizing errors in the capture and transmission of data (Belanger et al., 2011).

The delivery of effective, efficient, and quality patient care by CHWs[39] using mHealth tools is imperative to their monitoring, prevention and referral task performance. Therefore, the dimensions of effectiveness, efficiency and quality, will underscore user performance in the present study. As per theories of Attitude and Behaviour, use is determined by a set of precursors. These precursors are considered as determinants of use besides the 'Fit' between the Task performed and Technology used. These precursors of use are introduced in Section 5.5.

5.5 Precursors of Use in Task-Technology Fit (TTF) Research

Goodhue and Thompson (1995) extended their TTF model by including a set of precursors. They evaluated effects of these precursors as determinants of use besides TTF (p. 216). These determinants have been evaluated in TTF studies in various contexts. The precursors of use evaluated in TTF research have included dimensions such as social norms (D'Ambra and Wilson, 2004), accessibility (Goodhue et al., 1997), attitude toward system utilization (McGill and Hobbs, 2007), and facilitating conditions (McGill and Klobas, 2009). These and various other precursors of use specified in past TTF research are captured in Table 5.5. The theories of Attitude and Behaviour linking precursors to use are expanded upon in Chapter 10.

[39] Please refer Chapter 2 for a discussion of the contextual background of the present study.

Table 5.5. Precursors of Use in Task-Technology Fit (TTF) Research			
Construct	Dimension(s)	Context	Source
Precursors of Utilization	• Social norms • Control Factors	Use of Web Technologies for Travel	D'Ambra and Wilson (2004)
Accessibility	• Accessibility	Use of technologies in an information centre	Goodhue et al (1997)
Precursors of Utilization	• Expected Consequences of Use • Attitude Towards Using • Social Norms • Facilitating Conditions	Use of Virtual Learning Environments (VLEs)	McGill and Hobbs (2007)
Precursors of Utilization	• Expected Consequences of LMS Use • Attitude Towards LMS Use • Social Norms • Instructor Norms • Facilitating Conditions	Use of Learning Management Systems (LMSs)	McGill and Klobas (2009)
Precursors of Utilization	• Expected Consequences of Use • Affect Toward Use • Social Norms • Facilitating Conditions	Voluntary and Mandatory Tool Use	Staples and Seddon (2004)

Notably, precursors of use have not featured prominently in mobile technology and healthcare TTF research. Nevertheless, the above dimensions can be used to conceptualize precursors of technology use for the present study.

5.5.1 Precursors of Mobile-Health (mHealth) Technology Use

In previous TTF research, precursors of use are typically examined in institutional settings and much less in the more dynamic contexts of mobile technology and healthcare. For the present study, two precursors of mHealth technology use are considered.

First, *facilitating conditions* are support factors in the user environment that are conducive to technology use (Thompson et al., 1991). For example, supporting resources e.g. user training, have been observed to facilitate the use of ITs (McGill and Hobbs, 2007).

Second, *affect toward use* is the extent to which the user has a liking for the technology (Compeau, Higgins and Huff, 1999). The positive affect of users towards use e.g.

enjoyment, is expected to enhance the use of ITs. Conversely, the negative affect of users e.g. apprehension, could undermine their use of ITs (McGill and Klobas, 2009).

Having conceptualized the constructs of TTF, use, user performance, and precursors of use, the conceptual TPC model developed for testing in the present study is presented in Section 5.6.

5.6 The Conceptual Technology-to-Performance Chain (TPC) Model

The conceptual model, a TPC (Goodhue, 1992; Goodhue and Thompson, 1995) that is developed to link TTF, use, user performance, and precursors of use, is depicted in Figure 5.12.

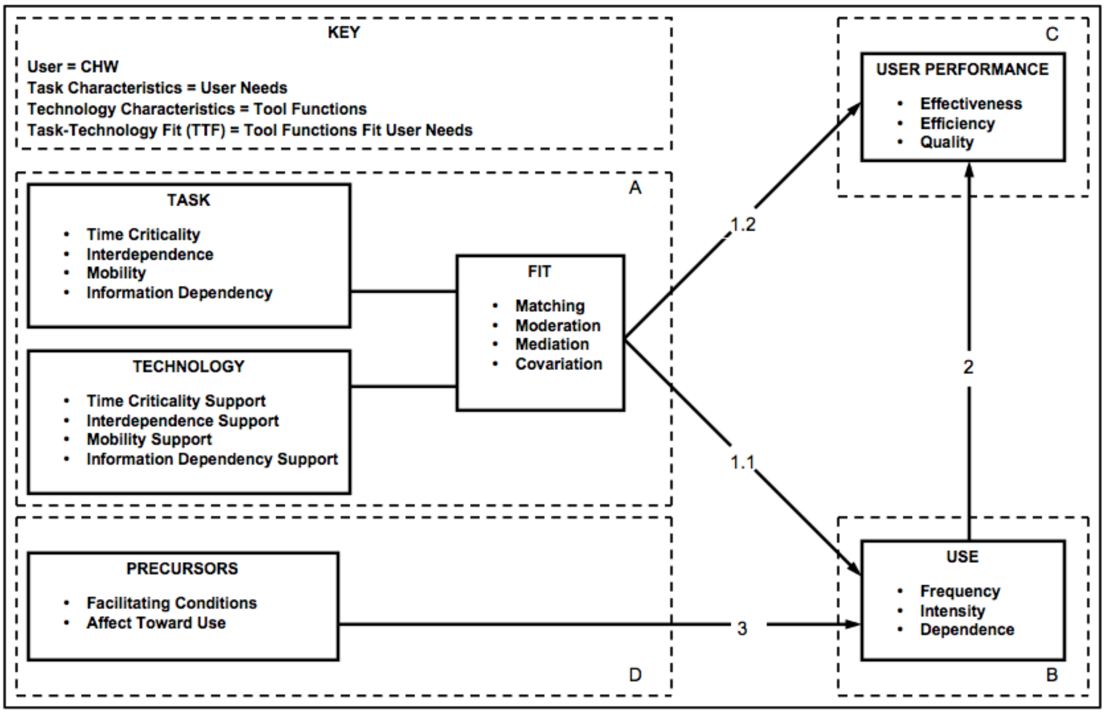

Figure 5.12. Conceptual Model

This conceptual model comprises the four constructs of TTF (A), use (B), user performance (C), and precursors of use (D). These constructs are components of the TPC. TTF is the core TPC component, linked first to use (Link 1.1) and second to user performance (Link 1.2). The TTF outcomes of use and user performance are concurrent. As per the traditional TTF (Fit-Focus) model (Goodhue and Thompson, 1995), technological support of the task is expected to influence both use and user performance.

TTF is conceptualized using four perspectives of ‘fit’ (Venkatraman, 1989) operationalized as Matching, Moderation, Mediation, and Covariation. Third, use is linked to user performance (Link 2). The traditional TTF (Fit-Focus) model is thus extended to form a complete TPC, such that user performance is considered a function of both TTF and use (Goodhue, 1992; Goodhue and Thompson, 1995, p. 216). Fourth, precursors are linked to use (Link 3). The completed TPC is thus extended, such that use is considered a function of both TTF and a set of precursors (Goodhue, 1992, p. 305).

5.7 Conclusion

The purpose of this chapter was to develop an empirically testable TPC linking task and technology characteristics to use and user performance through four perspectives of ‘fit’ (Venkatraman, 1989).

The four task characteristics of ‘time criticality’, ‘interdependence’, ‘mobility’, and ‘information dependency’, and the four technology characteristics of ‘time criticality support’, ‘interdependence support’, ‘mobility support’, and ‘information dependency support’, were surfaced as relevant in the context of mHealth tool use and CHW performance. Use and user performance are multi-dimensional constructs. User performance consists of ‘effectiveness’, ‘efficiency’, and ‘quality’ dimensions, and use encompasses ‘frequency’, ‘intensity’, and ‘dependence’ dimensions. In addition, use is positioned as mediating between a set of precursors, namely ‘facilitating conditions’ and ‘affect toward use’, and user performance.

The TPC developed for the present study is tested in Chapters 6 to 10. The effects of TTF as Matching, Moderation, Mediation, and Covariation, on use and user performance, are tested in Chapters 6 to 9. The effects of use as a determinant of user performance, and TTF and precursors as determinants of use, are tested in Chapter 10. The results of these tests of the TPC, and derived implications for research and practice are discussed in Chapter 11.

In chapter 1, a need for rigorous research to inform the design of mobile technologies that fit the needs of CHWs and enhance their task performance was established (Global Health Workforce Alliance, 2010). Consequently the following research questions were formulated:

3. How can a fit between mHealth tools and CHW tasks be conceptualized?
4. To what extent does this fit impact mHealth tool use and CHW performance?

The purpose of Chapters 6 to 9 is to address Research Questions 3 and 4 by examining the implications of Task-Technology Fit (TTF) for mHealth tool use and CHW performance from the 'fit' perspectives of Matching, Moderation, Mediation, and Covariation (Venkatraman, 1989). In Chapter 6, the effects of TTF as Matching on use and user performance are examined.

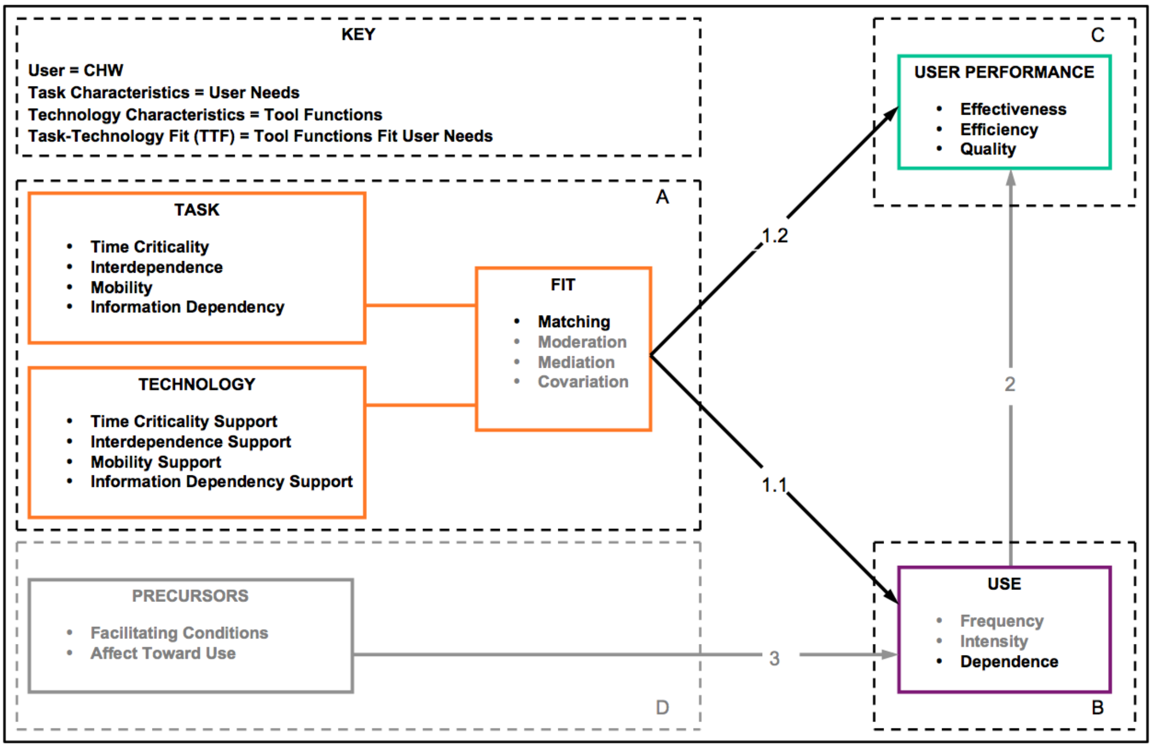

Figure 5.13. Task-Technology Fit (TTF) as Matching

6 The Effect of Task-Technology Fit (TTF) as Matching on Use and User Performance

This chapter is an updated version of Gatara, M. and Cohen, J.F (2015) Matching Task and Technology Characteristics to Predict mHealth Tool Use and User Performance – A Study of Community Health Workers in the Kenyan Context, *Proceedings of the 8th International Conference on Health Informatics (HEALTHINF)*, Lisbon, Portugal, pp. 454-461.

6.1 Introduction

The purpose of this chapter is to employ the Fit as Matching perspective (Venkatraman, 1989) to examine the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. First, 'fit' is conceptualized as comprising four sets of matching CHW task and mHealth technology characteristics. Second, using data collected from CHWs operating in Kenya, these matched task and technology characteristics are examined for their effects on CHWs' self-reported mHealth tool use and user performance outcomes.

6.2 Task-Technology Fit (TTF) as Matching

In prior works, Task-Technology Fit (TTF) has been defined as the matching of functional tool capacity with user activity demands (Dishaw and Strong, 1998b, p. 109). From this perspective, TTF as Matching is thus the pairing of corresponding user needs and tool functions. These paired needs and functions are complementary characteristics that can be configured using a TTF matrix (Dishaw, 1994, p. 37). Figure 6.1 depicts the TTF matrix representing the paired task and technology characteristics relevant to the mHealth tool context under study. These task and technology characteristics were described in detail in Section 5.3 of Chapter 5. Task characteristics are the features of a work task that reflect the task performer's job demands or needs (Dishaw, 1994), whereas technology characteristics are the supporting features or functions of the tool used to perform the task (Dishaw and Strong, 1998b). In Figure 6.1, the corresponding pairs of CHW task and mHealth technology characteristics are shaded, forming a diagonal in the TTF matrix.

Technology (Tool Function)

Task (User Need)

	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	FIT			
Interdependence		FIT		
Mobility			FIT	
Information Dependency				FIT

Figure 6.1. Task-Technology Fit (TTF) Matrix: Matching

Although Venkatraman (1989) originally specified the Fit as Matching perspective without reference to a criterion variable, the consequent effects of matching on specified outcomes can however be examined (p. 430). The link between TTF as Matching and use and user performance is discussed in Section 6.3.

6.3 Conceptual Model

6.3.1 The Link between Task-Technology Fit (TTF) as Matching and Use and User Performance

TTF theory is based on the premise that ‘fit’ as the matching of task and technology characteristics impacts use and user performance (Dishaw, 1994). This theorized link between TTF as Matching and use and user performance is shown in Figure 6.2.

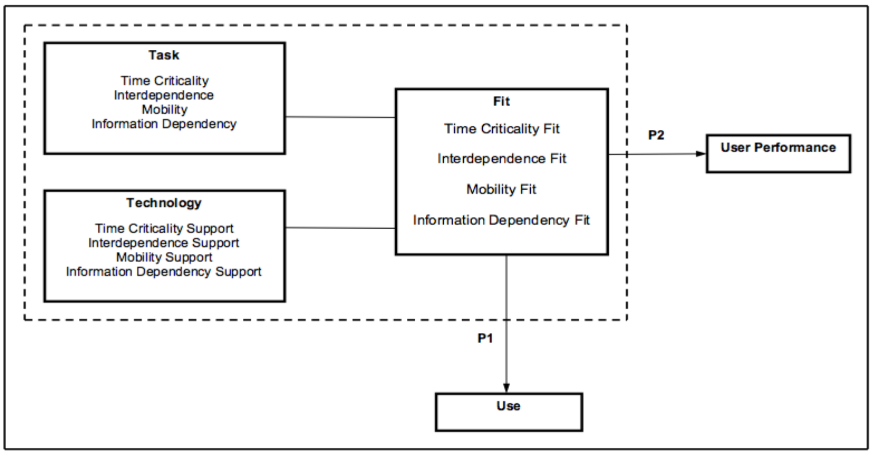

Figure 6.2. The Link between Task-Technology Fit (TTF) as Matching and Use and User Performance

According to TTF theory, if the technology matches the task performed, then use is stimulated and user performance should improve. This is because the technology used would directly complement the task performed such that tool functions would match user needs. For use and user performance to be optimized, there must be a match between user activities and tool functionality (Dishaw, 1994). In the mHealth context, 'fit' as the matching of CHW task characteristics (needs) and mHealth tool characteristics (functions) should similarly improve use and user performance. For example, a CHW may have to perform a high time criticality task such as the referral of a patient to a clinic for emergency care (Liu et al., 2011). The mHealth tool can functionally match this need by transmitting automated emergency SMS notifications or reminders (DeRenzi et al., 2011). As another example, a CHW may have a high information dependency task such as the monitoring of households when conducting disease surveillance (Braun et al., 2013). The mHealth tool can match this need with functionality such as interactive mapping to enable access to data on household locations (Yuan et al., 2010). As a consequence of such paired task-technology matches, CHWs are expected to become more dependent on using their mHealth tool to more effectively and efficiently deliver patient care with improved quality. The following propositions linking TTF as Matching to use and user performance are therefore formulated:

Proposition 1 (P1): *Fit as the match between CHW task characteristics and mHealth tool characteristics will influence mHealth tool use.*
Proposition 2 (P2): *Fit as the match between CHW task characteristics and mHealth tool characteristics will influence CHW performance.*

The following sub-propositions are derived:

Proposition 1a (P1a): *Fit as the match between time criticality of CHW tasks and time criticality support of the mHealth tool will influence use.*
Proposition 2a (P2a): *Fit as the match between time criticality of CHW tasks and time criticality support of the mHealth tool will influence user performance.*
Proposition 1b (P1b): *Fit as the match between interdependence of CHW tasks and interdependence support of the mHealth tool will influence use.*
Proposition 2b (P2b): *Fit as the match between interdependence of CHW tasks and interdependence support of the mHealth tool will influence user performance.*

Proposition 1c (P1c): *Fit as the match between mobility of CHW tasks and mobility support of the mHealth tool will influence use.*

Proposition 2c (P2c): *Fit as the match between mobility of CHW tasks and mobility support of the mHealth tool will influence user performance.*

Proposition 1d (P1d): *Fit as the match between information dependency of CHW tasks and information dependency support of the mHealth tool will influence use.*

Proposition 2d (P2d): *Fit as the match between information dependency of CHW tasks and information dependency support of the mHealth tool will influence user performance.*

The methods used to examine the impact of TTF as Matching on use and user performance are discussed in Section 6.4.

6.4 Methods

6.4.1 Sampling, Instrument, and Measures

Dataset 1 (n = 201) is used in this chapter. Dataset 1 is described in detail in Section B.1 of Appendix B. The dataset consists of responses from CHW mHealth tool users in the counties of Siaya, Nandi, and Kilifi. A structured questionnaire survey instrument was used to collect the data. The measures for CHW task characteristics, mHealth technology characteristics, use and user performance, were developed as described in Appendix E. These constructs were tested for multi-collinearity, reliability and validity, and final measures were used in subsequent analyses as per the procedures and criteria outlined in in Sections G.1 and G.2 of Appendix G.

6.4.2 Task-Technology Fit (TTF) as Matching

TTF as Matching was operationalized as the product indicator[40] of corresponding task (user need) and technology (tool function) characteristics. This was computed using the following equation (1):

$$\text{Fit}^{\text{MATCH } IJ} = \text{Task Characteristic } I \times \text{Technology Characteristic } J \qquad (1)$$

where:

[40] Per Venkatraman (1989, p. 424), interaction terms representing matching fit variables were computed.

Fit $^{MATCH\ IJ}$ = Task-Technology Fit (TTF) of mHealth technology characteristic *J* to CHW task characteristic *J*

I = Supporting Technology Characteristic (Tool Function)

J = Task Characteristics (User Need)

The four matches of CHW task (need) and mHealth tool (function) characteristics were computed as interaction terms (Henseler and Fassott, 2010, p. 723) using equation 1. The TTF matrix in Figure 6.1 can be modified to capture each corresponding user need and tool function as a product term. This modified TTF matrix, with each matching pair represented as a product term, is shown in Figure 6.3.

Technology (Tool Function)

Task (User Need)	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	TC x TCS FIT			
Interdependence		I x IS FIT		
Mobility			M x MS FIT	
Information Dependency				ID x IDS FIT

Figure 6.3. Task-Technology Fit (TTF) Matrix: Computed Matching

The four matching pairs of CHW task characteristics and mHealth tool function characteristics were *time criticality fit*, *interdependence fit*, *mobility fit*, and *information dependency fit*.

Partial Least Squares - Structural Equation Modeling (PLS - SEM) was used to test the effects of TTF as Matching on use and user performance (Hair, Hult, Ringle and Sarstedt, 2014). The indicator values expressed in Equation (1) were mean-centered prior to multiplication. This was necessary because centering predictor variables greatly lessens multi-collinearity when using multiplicative terms to model moderating effects (Henseler and Fassott, 2010, p. 728). First, a structural path model was estimated to test the effect of each match of task and technology characteristics, on use and user performance. Interaction effects were then plotted for TTF matches found to be significant for the prediction of use or user performance. Second, a structural path model was estimated to test the simultaneous effect of multiple matches of task and technology characteristics, on use and user performance. This test was necessary because as Dishaw (1994) observed, tool users are capable of performing tasks simultaneously or in parallel (p. 37). Coefficients of determination (R^2 values) of the endogenous constructs use and user performance were used to determine the predictive accuracy[41] of the PLS structural path models (Hair et al., 2014, p. 174), and Stone-Geisser's Q^2 values (Geisser, 1974; Stone, 1974) of use and user performance were used to determine their predictive relevance[42] (Hair et al., 2014, p. 178). In addition, f^2 (q^2) effect sizes[43] were computed to determine relative impacts of each matching pair of task and technology characteristics on the predictive accuracy (R^2) and relevance (Q^2) of the PLS structural path models (Urbach and Ahlemann, 2010; Hair et al., 2014). Results of the structural path model estimates of TTF as Matching are discussed in Section 6.5.

6.5 Results

The structural path models estimated to test TTF matching effects of *time criticality fit (model A)*, *interdependence* fit *(model B)*, *mobility fit (model C)*, and *information dependency fit (model D)*, are depicted in Figure 6.4.

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41 R^2 values of approximately 0.670, 0.333, and 0.190 are substantial, moderate, and weak, respectively (Chin, 1998; Urbach and Ahlemann, 2010, p. 21).
42 Q^2 values larger than zero for a certain reflective endogenous latent variable are indicators of predictive relevance (Henseler et al., 2009, Hair et al., 2014, p. 178).
43 For f^2, values of 0.02, 0.15, and 0.35 are small, medium, and large effects, respectively (Cohen, 1988). These threshold values are also used to assess q^2 (Urbach and Ahlemann, 2010; Hair et al., 2014).

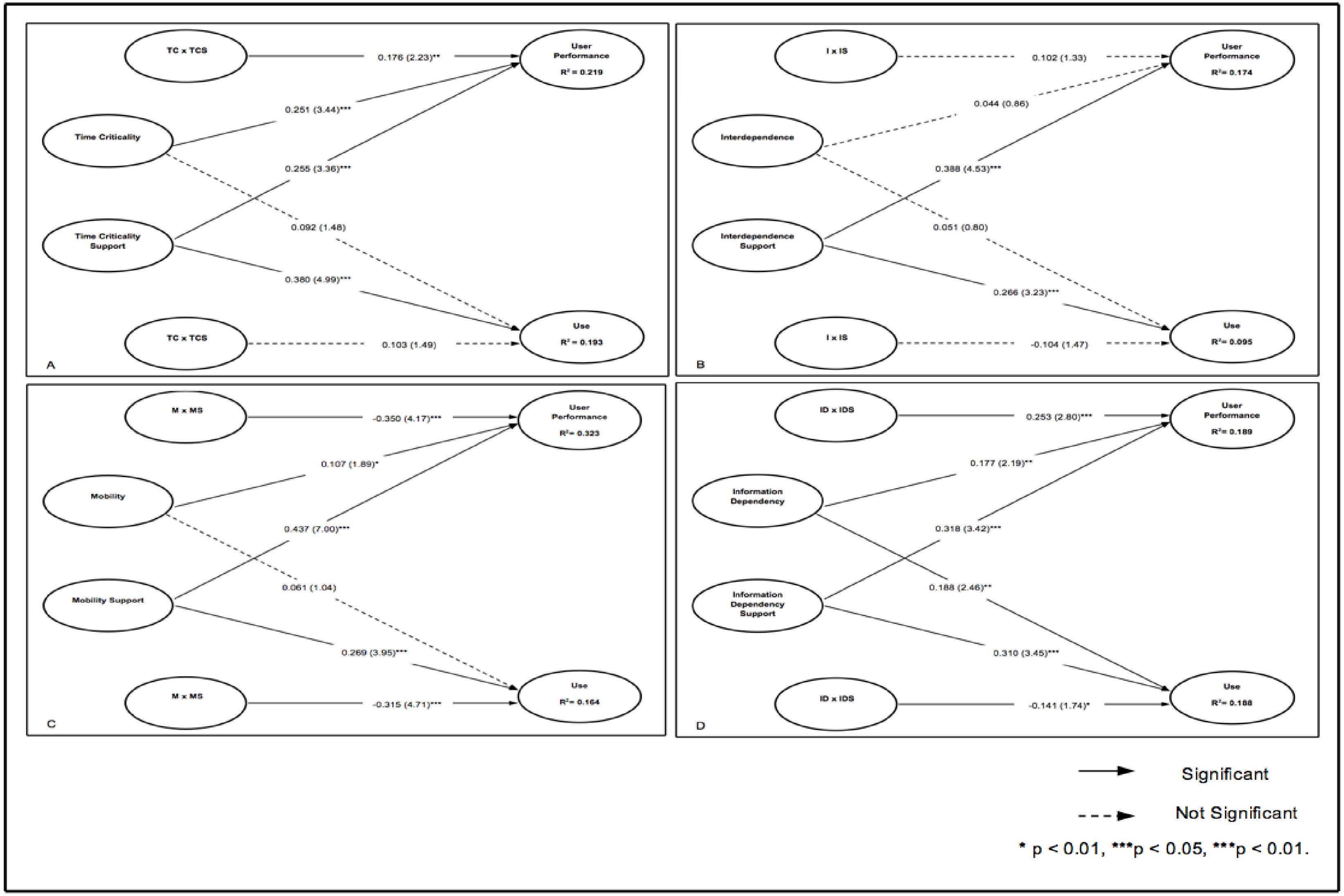

Figure 6.4. Path Models: Task-Technology Fit (TTF) as Matching

Results including *t* values, *p* values, significance levels, and confidence intervals, of the four structural path models estimated to test the effect of *time criticality fit (model A)*, *interdependence fit (model B)*, *mobility fit (model C)*, and *information dependency fit (model D)*, on *use* and *user performance*, are presented in Table 6.1.

Table 6.1. Structural Path Model Results					
Path	**Path Coefficient**	***t***	***p***	**Significance**	**90% CI**
Model A: Time Criticality Fit					
Time Criticality → Use	0.092	1.48	0.14	NS	[-0.01, 0.20]
Time Criticality Support → Use	0.380	4.99	0.00	***	[0.25, 0.50]
*Time Criticality x Time Criticality Support (TC * TCS) → Use*	0.103	1.49	0.14	NS	[-0.01, 0.22]
R^2 = 0.193, f^2 *(TC * TCS) → Use* = 0.01, Q^2 = 0.097, q^2 *(TC * TCS) → Use* = 0.08					
Time Criticality → User Performance	0.251	3.44	0.00	***	[0.13, 0.37]
Time Criticality Support → User Performance	0.255	3.36	0.00	***	[0.13, 0.38]
*Time Criticality x Time Criticality Support (TC * TCS) → User Performance*	0.176	2.23	0.03	**	[0.05, 0.31]
R^2 = 0.219, f^2 *(TC * TCS) → User Performance* = 0.04, Q^2 = 0.135, q^2 *(TC * TCS) → User Performance* = 0.02					
Model B: Interdependence Fit					
Interdependence → Use	0.051	0.80	0.42	NS	[-0.05, 0.15]
Interdependence Support → Use	0.266	3.23	0.00	***	[0.13, 0.40]
*Interdependence x Interdependence Support (I * IS) → Use*	-0.104	1.47	0.14	NS	[-0.22, 0.01]
R^2 = 0.095, f^2 *(I * IS) → Use* = 0.01, Q^2 = 0.049, q^2 *(I * IS) → Use* = 0.01					
Interdependence → User Performance	0.044	0.86	0.39	NS	[-0.04, 0.13]
Interdependence Support → User Performance	0.388	4.53	0.00	***	[0.25, 0.53]
*Interdependence x Interdependence Support (I * IS) → User Performance*	0.102	1.33	0.19	NS	[-0.02, 0.23]
R^2 = 0.174, f^2 *(I * IS) → User Performance* = 0.01, Q^2 = 0.100, q^2 *(I * IS) → User Performance* = 0.00					
Model C: Mobility Fit					
Mobility → Use	0.061	1.04	0.30	NS	[-0.04, 0.16]
Mobility Support → Use	0.269	3.95	0.00	***	[0.16, 0.38]
*Mobility x Mobility Support (M * MS) → Use*	-0.315	4.71	0.00	***	[-0.42, -0.21]

R^2 = 0.164, f^2 *(M * MS) → Use* = 0.11, Q^2 = 0.097, q^2 *(M * MS) → Use* = 0.07					
Mobility → User Performance	0.107	1.89	0.06	*	[0.01, 0.20]
Mobility Support → User Performance	0.437	7.00	0.00	***	[0.33, 0.54]
*Mobility x Mobility Support (M * MS) → User Performance*	-0.350	4.17	0.00	***	[-0.49, -0.21]
R^2 = 0.323, f^2 *(M * MS) → User Performance* = 0.17, Q^2 = 0.193, q^2 *(M * MS) → User Performance* = 0.08					
Model D: Information Dependency Fit					
Information Dependency → Use	0.188	2.46	0.02	*	[0.06, 0.31]
Information Dependency Support → Use	0.310	3.45	0.00	***	[0.16, 0.46]
*Information Dependency x Information Dependency Support (ID * IDS) → Use*	-0.141	1.74	0.08	*	[-0.27, -0.01]
R^2 = 0.188, f^2 *(ID * IDS) → Use* = 0.03, Q^2 = 0.095, q^2 *(ID * IDS) → Use* = 0.02					
Information Dependency → User Performance	0.177	2.19	0.03	**	[0.05, 0.31]
Information Dependency Support → User Performance	0.318	3.42	0.00	***	[0.17, 0.47]
*Information Dependency x Information Dependency Support (ID * IDS) → User Performance*	0.253	2.80	0.01	**	[0.11, 0.40]
R^2 = 0.189, f^2 *(ID * IDS) → User Performance* = 0.07, Q^2 = 0.117, q^2 *(ID * IDS) → User Performance* = 0.04					

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01

6.5.1 Time Criticality Fit

Time criticality fit is the match between time criticality as a CHW task characteristic (user needs) and time criticality support as a technology characteristic (tool functions). Results in Table 6.1 indicate that a match between the *time criticality* of tasks and *time criticality support* of the mHealth tool has a significant positive effect (path coefficient = 0.176, t = 2.23, $p < 0.05$) on *user performance*. Matching *time criticality support* (tool function) to *time criticality* (user need) task characteristics leads to increased *user performance*. ***Proposition 2a (P2a)*** is supported. However, a match between *time criticality* of tasks and *time criticality support* of the mHealth tool does not have a significant effect on actual *use*. Whereas this match may lead to higher *user performance* levels, it does not appear to be important for explaining *use*. The graph in Figure 6.5 shows the effects of the matched-pair interaction between *time criticality* (needs) and *time criticality support* (tool functions) on *user performance*.

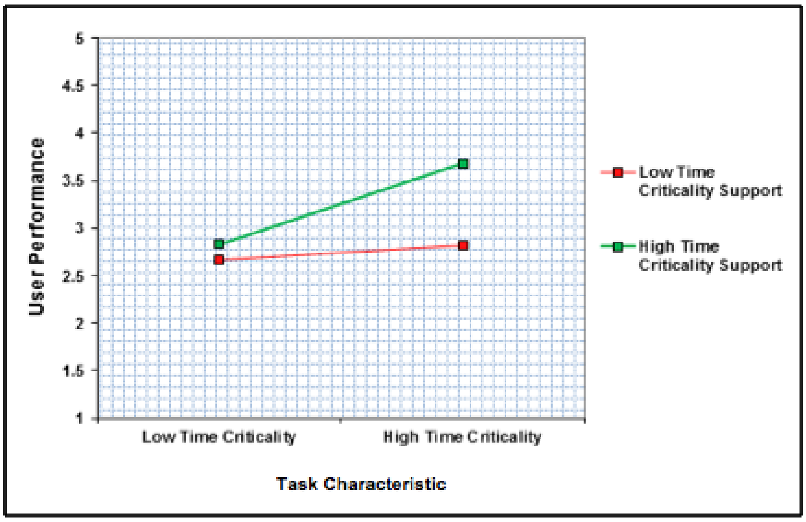

Figure 6.5. Time Criticality Fit: Interaction Effects on User Performance

The graph shows that CHWs who have a high need to respond urgently during emergencies, and for whom delivery of patient care is time critical, will perform better when mHealth tools provide support for time criticality through functions such as scheduled SMS-based notifications or automated alerts (Liang and Wei, 2004; Yuan et al., 2010; DeRenzi et al., 2012). However, high need users who perceive lower functional support levels from their mHealth tool report lower levels of user performance.

6.5.2 Interdependence Fit

Interdependence fit is the match between interdependence as a CHW task characteristic (user needs) and interdependence support as a technology characteristic (tool functions). Results in Table 6.1 indicate that contrary to expectations, matching *interdependence* and *interdependence support* does not have significant effects on *use* and *user performance.* ***Propositions 1b (P1b)*** and ***2b (P2b)*** were not supported. Notably, *interdependence support* had a significant positive effect on *use* (path coefficient = 0.266, t = 3.23, p < 0.01) and *user performance* (path coefficient = 0.388, t = 4.53, p < 0.01). Despite the absence of an *interdependence* need, the presence of *interdependence support* functions is sufficient for a higher dependence among CHWs on mHealth tool use and the more effective and efficient delivery of higher quality patient care attributed to the tool.

6.5.3 Mobility Fit

Mobility fit is the match between *mobility* as a CHW task characteristic (user needs) and *mobility support* as a technology characteristic (tool functions). Results in Table 6.1 indicate that matching *mobility* (user need) and *mobility support* (tool function) characteristics has a significant negative effect (path coefficient = -0.135, t = 4.71, p < 0.01) on *use*. Similarly, the matching of *mobility* (need) and *mobility support* (tool function) characteristics has a significant negative effect (path coefficient = -0.350, t = 4.17, p < 0.01) on *user performance*. Despite their significance, these effects are not consistent with ***Proposition 1c (1c)*** and ***Proposition 2c (P2c)*** as they are not in the expected direction. The graphs in Figures 6.6 and 6.7 show the effects of the matched-pair interactions of *mobility* and *mobility support* on *use* and *user performance* respectively.

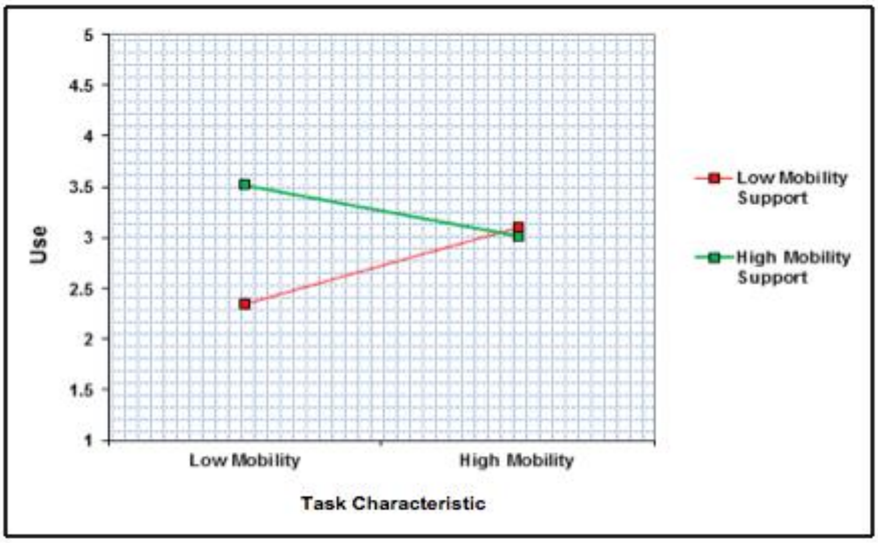

Figure 6.6. Mobility Fit: Interaction Effects on Use

Figure 6.6 shows that for CHWs with high task mobility, dependence on the tool is not contingent on the characteristics of the technology. It is only among CHWs with low task mobility that dependence on the tool is contingent on the characteristics of the technology. This is most likely because the nature of CHW work dictates that regardless of tool support, CHWs are highly mobile anyway, and are therefore much less likely to become more dependent on the tool. But those who perhaps less regularly enter the field or do less outreach may rely more on the tool.

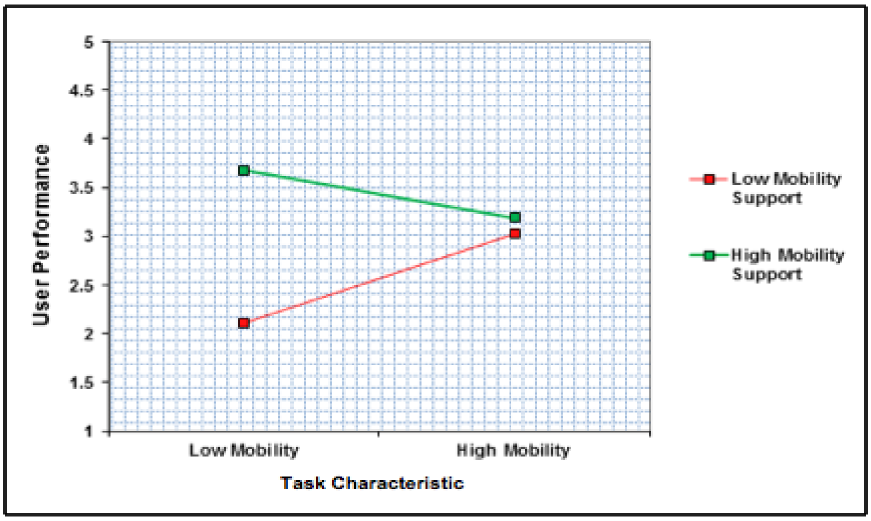

Figure 6.7. Mobility Fit: Interaction Effects on User Performance

Figure 6.7 shows that the performance of CHWs with relatively little task mobility (typically travel less from one location to another) is however contingent on the tool such that they perform better with more functionality. This indicates that supporting CHWs with higher mobility needs is less successful than those with lower mobility needs. This is most likely because most CHWs will need mobility regardless of tool support because it is inherent to the nature of their work. As such, only the less mobile appear to rely on the tool to improve performance in the field.

6.5.4 Information Dependency Fit

Information dependency fit is the match between *information dependency* as a CHW task characteristic (user needs) and *information dependency* support as a technology characteristic (tool functions). Results in Table 6.1 indicate that matching *information dependency* (user need) and *information dependency* (tool function) characteristics has a significant positive effect on *user performance* (path coefficient = 0.253, t = 2.80, $p < 0.05$). ***Proposition 2d (P2d)*** was supported. However, matching *information dependency* (user need) and *information dependency* (tool function) characteristics has a significant negative effect on *use* (path coefficient = -0.141, t = 1.74, $p < 0.10$). Despite its significance, this effect is not consistent with ***Proposition 1d (P1d)*,** since it is not in the expected direction. The graphs in Figures 6.8 and 6.9 show effects of the matched-pair interaction between *information dependency* of CHW tasks and mHealth support for *information dependency* (tool functions) on *use* and *user performance* respectively.

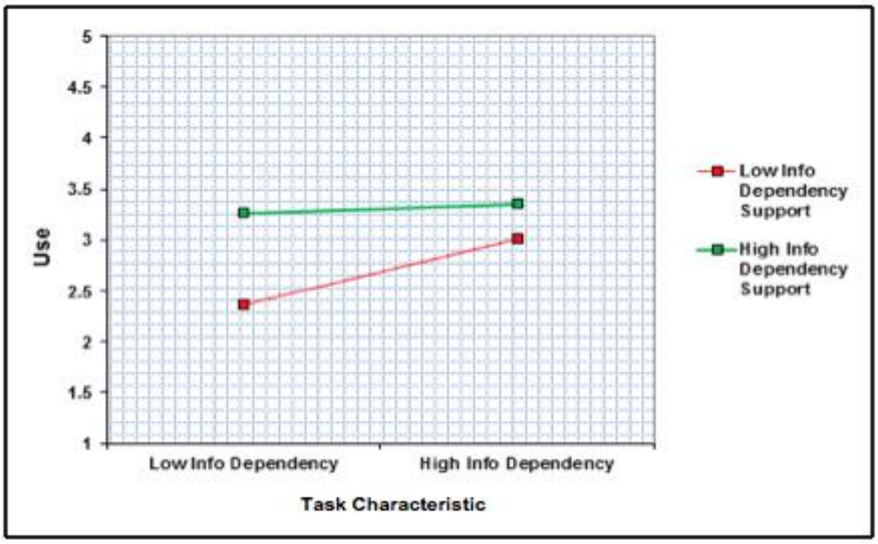

Figure 6.8. Information Dependency Fit: Interaction Effects on (a) Use

The graph in Figure 6.8 shows that user dependence on the tool is highest among those CHWs with a high level of information dependency and a tool that provides matched support. Some users with a low information dependency need and who don't then investigate the functional support offered by the tool, will not come to depend on the tool in their work. Some users with high information dependency may be struggling to also have those dependency needs met by the tool but they persevere with tool use non-the-less.

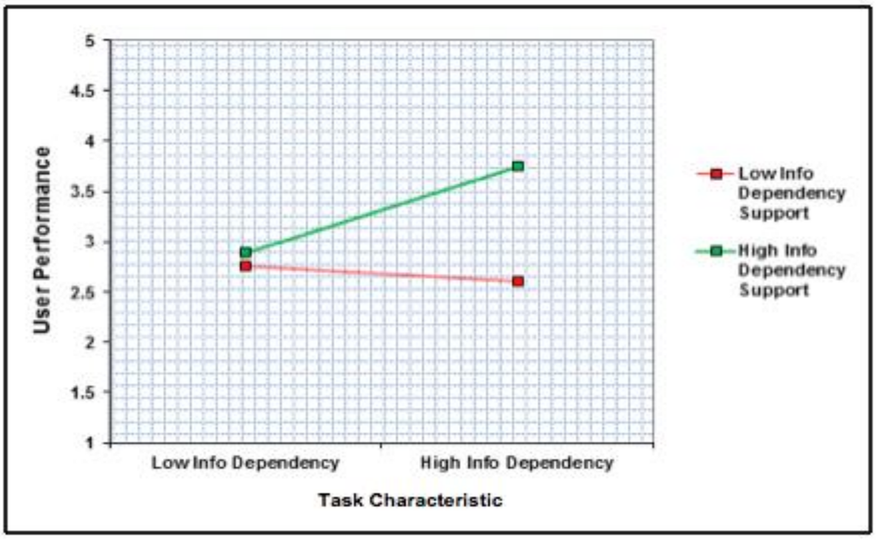

Figure 6.9. Information Dependency Fit: Interaction Effects on (a) User Performance

The graph in Figure 6.9 similarly shows that the highest performers are CHWs with high information dependency tasks and a tool that provides matching support. However, some users with high information dependency needs are struggling to perceive those dependency needs supported by the tool's functionality, and are thus likely to become frustrated and report lower levels of user performance. CHWs with high information dependency are not able to deliver high quality care, more efficiently and effectively if they perceive that their tool lacks support for their information needs. These CHWs report the lowest performance.

6.5.5 Combined Matching

The combined effects of matched-pairs *time criticality fit*, *interdependence fit*, *mobility fit*, and *information dependency fit*, on *use* and *user performance* was also examined. The structural path model estimated to test the simultaneous effects of all the four matched-pairs on *use* and *user performance* is presented in Figure 6.10. The model has significant predictive accuracy for the endogenous constructs of *use* (R^2 = 0.309) and *user performance* (R^2 = 0.466), respectively. The model also has significant predictive relevance for the endogenous constructs of *use* (Q^2 = 0.181) and *user performance* (Q^2 = 0.290) as Q^2 *values* are above 0 (Hair et al., 2014, p. 178). Figure 6.10 shows that all of the mHealth tool characteristics are significant for *user performance* along with *time criticality fit*, *mobility fit*, and *information dependency fit* matched-pairs. The CHW task characteristics *time criticality support* and *information dependency support* are significant for *use* along with the *mobility fit* and *information dependency fit* matched-pairs.

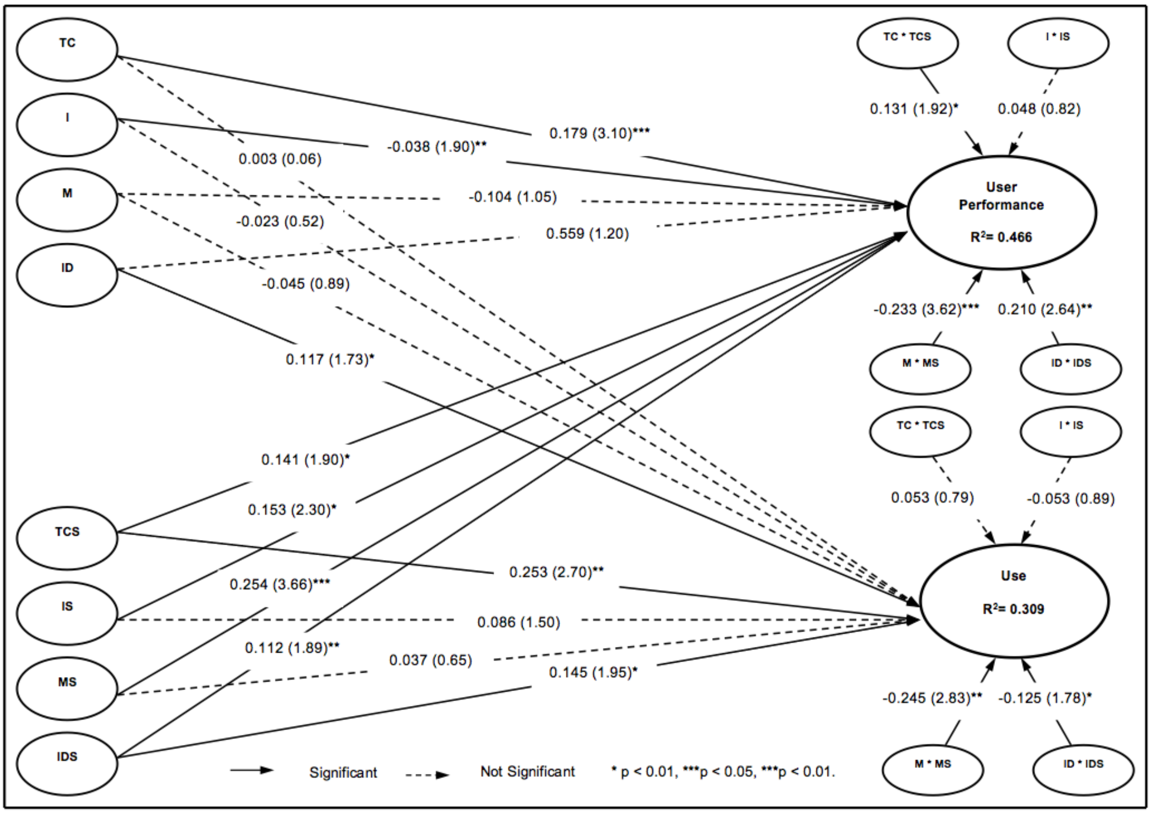

Figure 6.10. Path Model – Task-Technology Fit (TTF) as Matching: Simultaneous Effect

The path coefficients, *t* values, *p* values, f^2 (q^2) effects, and significance levels of the structural path model estimated to test a combined matching fit are summarized in Table 6.2.

Table 6.2. Results: Combined Matching Effects

Predictor (Matching Pair)	**Endogenous Construct**					
	Use			**User Performance**		
	Path Coefficient	f^2	q^2	**Path Coefficient**	f^2	q^2
*Time Criticality x Time Criticality Support (TC * TCS)*	0.053 (0.79 NS)	0.00	0.01	0.131 (1.92 *)	0.03 S	0.01
*Interdependence x Interdependence Support (I * IS)*	-0.053 (0.89 NS)	0.00	0.01	0.048 (0.82)	0.00	-0.00
*Mobility x Mobility Support (M * MS)*	-0.245 (2.83 **)	0.08 S	0.04 S	-0.233 (3.62 ***)	0.09 S	0.03 S
*Information Dependency x Information Dependency Support (ID * IDS)*	-0.125 (1.78 *)	0.02 S	0.02 S	0.210 (2.64 **)	0.07 S	0.04 S
R^2 (Use) = 0.309, Q^2 (Use) = 0.181, R^2 (User Performance) = 0.466, Q^2 (Use Performance) = 0.290						

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01, S = Small Effect

6.6 Discussion

6.6.1 Time Criticality Fit

A match between CHW perceptions of the mHealth tool's time criticality support and the task need for time criticality does not have significant effects on use. CHW dependence on the mHealth tool is therefore not contingent upon this match. This fit pairing, however, significantly influences user performance. It is observed that matching functional support to the CHW need to respond urgently, e.g. during emergencies, leads to CHW delivery of higher quality patient care, more effectively and efficiently. Junglas, Abraham, and Ives (2009) similarly observed that in a hospital setting, a time criticality fit was not particularly important for nurse dependence on mobile technology (p. 641), but that utilizing a system that generated timely emergency notifications improved nursing performance (p. 642). The finding in this study is consistent and supports the notion that for effective patient care in time-sensitive scenarios, health workers require timely notifications (p. 635). It is also instructive to note that during emergencies in health settings, a lack of access to timely notifications has been observed to adversely affect patient care delivery (Junglas et al., 2009).

6.6.2 Interdependence Fit

Matching interdependence support of the mHealth tool to the CHW task need to co-operate with co-workers does not have significant effects on either use or user performance. CHW dependence on the mHealth tool for effective and efficient delivery of quality patient care is not conditional upon this match. It appears that CHWs tend to co-operate through established interpersonal relationships, informally co-ordinating and exchanging information. The notion that CHW co-workers would instantly adapt to mHealth tools for this purpose and disrupt their established mechanisms for facilitating interdependence is thus not reinforced. This non-significant finding corroborates Teo and Men's (2008) observation that system utilization is often incompatible with existing work practices and that collaborating co-workers in a particular setting may prefer their more traditional customs of interpersonal contact (p. 569). This finding, however, contradicts Dishaw and Strong (1998b) who observed that similarly matching co-ordination tool functionality to co-ordination task activities, contributes to increased tool utilization (p. 115), although their study was situated in a software development setting. It is thus evident that the significance or non-significance of an interdependence match for use and performance is context-sensitive.

6.6.3 Mobility Fit

A match of mobility support as an mHealth tool function to the CHW need for manoeuvrability has an unexpected negative effect on both use and user performance. Contrary to expectations, this matched pair is associated with less CHW dependence on the mHealth tool, and lower performance, thus diminished effectiveness, efficiency, and quality in the delivery of patient care. Graphical plots of the interaction effects of this paired fit show that when there is high CHW task mobility, mHealth tool dependence and user performance are not contingent on technological support. However, in a low CHW task mobility environment, the tool used drives user dependence and task performance. As such, the importance of tool design is recognized as an essential contributor to a positive fit between mobile technology and the user's need for mobility (Junglas et al., 2009; p. 638). In a related study, Junglas, Abraham, and Ives (2009) observed that a similar construct, physical fit, was not found to be instrumental to mobile technology utilization and nursing performance (p. 641). It therefore appears that not every user may benefit from all mobile technology tools, especially when their tasks are information-intensive. The finding in this study however, contradicts Yuan, Archer, Connelly and Zheng's (2010) observation that a fit between mobility task needs and mobile work support characteristics leads to an increase in user intentions to use mobile systems (p. 131). Users who perceive the tool as more supportive of mobility than their tasks necessitate, are more likely to use it and perform better, while others who acknowledge the mobility demands of their work may attribute less of their performance to tool functionality. Evidently, not all mobile technology users in particular contexts necessarily enjoy the same advantages that accrue from a tool's supporting functionality.

6.6.4 Information Dependency Fit

The matching of information dependency support as an mHealth tool function to the CHW need to access information at the point-of-care has significant positive effects on user performance. This finding corroborates Junglas, Abraham, and Ives (2009) who established that data access for health workers was necessary for their effective patient care delivery (p. 637). However, the match had a negative impact on usage dependency such that CHWs are less dependent on using the mHealth tool to perform tasks. This contradicts Yuan, Archer, Connelly, and Zheng (2010) who observed that a fit between location dependence tasks and equivalent mobile technology support functions signified a positive utilization experience for workers (p. 131). CHWs who exhibit high information dependency are dependent on the tool even if they do not always perceive functional support. It is only those users who exhibit low information dependency who report low dependence on the tool and are less likely to consider the support it may provide for the information dependency characteristics of their work.

6.6.5 Simultaneous Fit as Matching

It has been acknowledged in prior research that the concept of 'fit' can assume a theoretically defined match between two related components (Venkatraman, 1989, p. 430). Bergeron, Raymond and Rivard (2001), however, recognized that 'fit' could also signify the matching of multiple pairs of related components (p. 127). The matching pairs of time criticality fit, interdependence fit, mobility fit, and information dependency fit, together, have significant effects on use and user performance. This indicates that at the point-of-care, functional mHealth tool support for CHW task needs can be simultaneously present. These results are indicative of the possible co-existence of multiple user needs and tool functions in a particular context. Thus the matching of two related components need not necessarily occur in isolation, but rather as a combination of paired characteristics in a shared user environment. Findings also indicate that matching pairs observed independently appear to retain their characteristic use and user performance effects even when observed collectively.

6.6.6 Implications for Research

There are two emergent implications for research arising from the findings discussed in this chapter.

First, a TTF matrix was used to configure the matching pairs of time criticality fit, interdependence fit, mobility fit, and information dependency fit, thus signifying the visual representation of complementary dimensions of TTF. This representation is particularly useful for researchers who seek to visualize matching user needs and tool functions. To depict primary matching pairs, Dishaw (1994) first introduced a TTF matrix. Since its inception however, this configurative approach only featured in one subsequent study (Dishaw and Strong, 1998b). Its use, therefore, signifies a renewed interest in TTF conceptualization.

Second, it was found that particular matching pairs may influence user performance whilst not being significant for use, not at all be significant for either use or user performance, have adverse effects on use and user performance for some users, and even negatively affect use whilst positively influencing user performance. These findings represent unique insights into the complexity of TTF matching in context, and can be useful for interpreting the magnitude and direction of its effects on tool dependence and task performance outcomes. It is apparent that despite the expectation of an ideal match, a positive pairing of user needs and tool functions may not always occur. These observed fit characteristics are not without precedent in previous research. Dishaw (1994) similarly found that in a maintenance task domain, some matching TTF pairs were associated with higher software tool use, whereas others negatively influenced levels of usage (p. 124). Researchers would therefore be better informed to anticipate and carefully observe the various ways in which a match between task and technology characteristics manifests.

6.6.7 Implications for Practice

There are two emergent implications for practice arising from the findings discussed in this chapter.

First, mHealth tool designers must focus more on CHW task characteristics when developing support functions. Enhanced support requires that there is first an acute awareness of critical CHW task requirements. The findings observed in this study therefore represent important practical insights to inform the design of responsive mHealth technologies that better support CHW tasks. CHWs may not necessarily be homogenous in their task needs.

Second, support functions that meet specific CHW needs must supersede the long-standing practice of merely automating technologies and imposing tools that do not complement user needs. To achieve complentarity, mHealth tool designers must endeavour to develop technologies that enable users to select and use task-specific support functionality.

6.7 Chapter Conclusion

The purpose of this chapter was to adapt Venkatraman's (1989) Fit as Matching perspective to test the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. Four pairs of matching task and technology characteristics were examined for their effects on mHealth tool use and CHW performance. First, time criticality fit was significant for CHW performance, but was not significant for mHealth tool use. Second, interdependence fit was neither significant for mHealth tool use nor CHW performance. Third, mobility fit unexpectedly had negative effects on mHealth tool use and CHW performance. It was found that only CHWs with relatively lower task mobility will depend more on the mHealth tool and perform better with its functionality. Fourth, information dependency fit similarly had negative effects on mHealth tool use. However, as expected, this matched fit was significant for CHW performance. Information dependency support of the mHealth tool to information dependency of tasks leads to even more effective and efficient delivery of patient care with more quality. The combined effects of the task, the technology and the four matched-pairs on mHealth tool use and CHW performance were also examined. These matched-pairs were found to be significant predictors of mHealth tool use and CHW performance. It was found that multiple pairs of corresponding CHW needs and mHealth tool functions, together influence dependence on the mHealth tool and patient care effectiveness, efficiency and quality. Moreover, it becomes apparent that in the context of the present study, a matching fit is not necessarily restricted to a single pair of corresponding task (user need) and technology (function) characteristics.

Results of tests of TTF as Matching and its effects on use and user performance are summarized in Table 6.3.

Table 6.3. Findings		
Proposition		Finding
P1	Fit as the match between task (need) and technology (tool function) characteristics will influence use.	Supported
P2	Fit as the match between task (need) and technology (tool function) characteristics will influence user performance.	Supported
P1a	Fit as the match between time criticality and time criticality support will influence use.	Not Supported
P1b	Fit as the match between time criticality and time criticality support will influence user performance.	Supported
P2a	Fit as the match between interdependence and interdependence support will influence use.	Not Supported
P2b	Fit as the match between interdependence and interdependence support will influence user performance.	Not Supported
P3a	Fit as the match between mobility and mobility support will influence use.	Negative Effects
P3b	Fit as the match between mobility and mobility support will influence user performance.	Negative Effects
P4a	Fit as the match between information dependency and information dependency support will influence use.	Negative Effects
P4b	Fit as the match between information dependency and information dependency support will influence user performance.	Supported

In Chapter 6, TTF as Matching and its effects on use and user performance was examined. In Chapter 7, TTF as Moderation and its effects on use and user performance is examined.

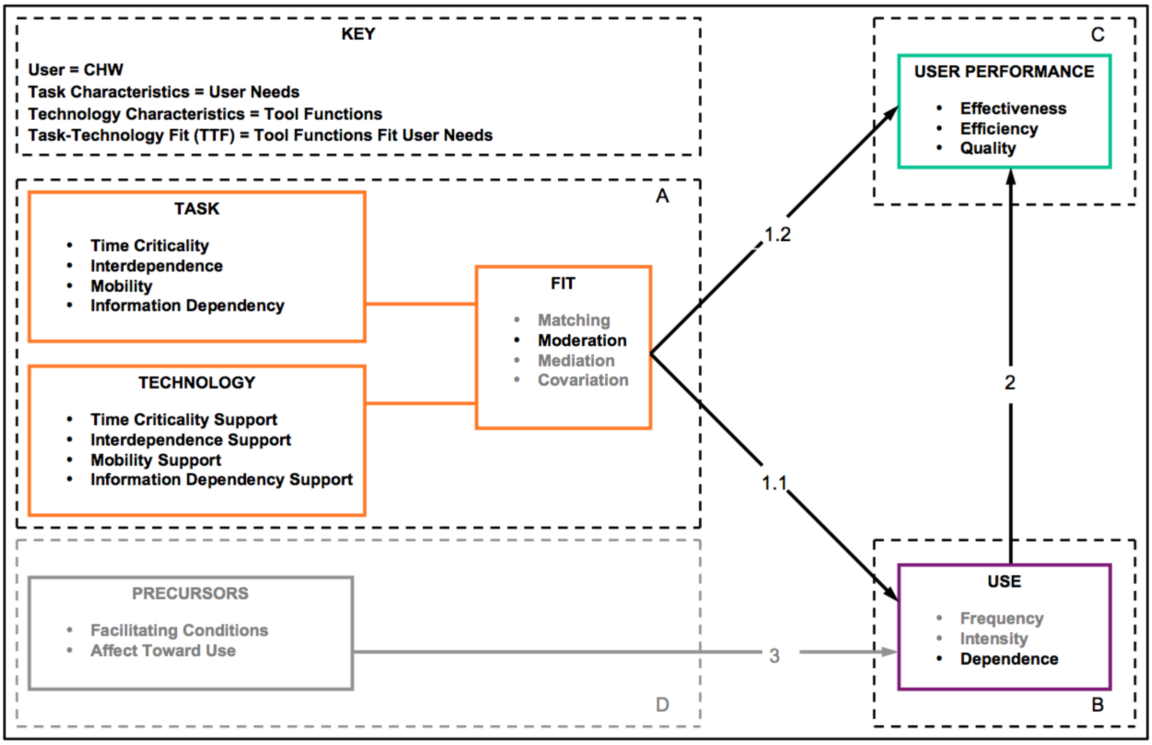

Figure 6.11. Task-Technology Fit (TTF) as Moderation

7 The Effects of Task-Technology Fit (TTF) as Moderation on Use and User Performance

This chapter is in part, published in Gatara, M. (2016) Mobile Health Tool Use and Community Health Worker Performance in the Kenyan Context: A Comparison of Task-Technology Fit Perspectives, in *mHealth Ecosystems and Social Networks in Healthcare*, Springer.

7.1 Introduction

The purpose of this chapter is to employ the Fit as Moderation perspective (Venkatraman, 1989) to examine the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. In Chapter 4, it was established that Fit as Moderation (Venkatraman, 1989) has been used to examine the effects of TTF in contexts such as the use of knowledge - portals for collaboration tasks (Teo and Men, 2008), surgical procedures in hospital settings (Schoonhoven, 1981), and engineering tools for software maintenance tasks (Dishaw, 1994). In this study, Fit as Moderation comprises sixteen sets of interacting CHW task and mHealth tool characteristics, each representing a cross-product term examined for effects on use and user performance. The concept of TTF as Moderation is discussed in Section 7.2.

7.2 Task-Technology Fit (TTF) as Moderation

In Chapter 6, the Fit as Matching perspective (Venkatraman, 1989) was used to conceptualize TTF as the pairing of corresponding task and technology characteristics. In this chapter, TTF is conceptualized from the perspective of Fit as Moderation (Venkatraman, 1989). From this perspective, TTF is defined as the cross-product interaction of all task and technology characteristics, then examined for its effects on mHealth tool use and CHW performance. This perspective is premised upon the impact of two variables, a predictor on a criterion, depending on the level of a third variable, the moderator (Venkatraman, 1989, p. 424). TTF as Moderation thus represents the effect of all task characteristics on use and user performance, depending on all functional support levels rendered. Therefore, the technology (tool functions) moderates the relationship between the tasks (needs), and use and user performance. Venkatraman (1989) conceptualized this moderating effect as an *interaction* (p. 438). In this study, the predictor is the CHW task characteristic, the criterion variables are use and user performance, and the moderator is the mHealth technology characteristic. As such, all task and technology characteristics interact. This interaction is reflected as a cross-product of these interacting task and technology characteristics. This is a 'fit' that captures both on-diagonal (matched) and off-diagonal (non-matched) interactions. This mode of interaction has been adopted elsewhere. For example, Teo and Men (2008) conceptualized TTF as the cross-product of Knowledge Management (KM) task and technology characteristics (p. 561). The TTF matrix (Dishaw, 1994; p. 37) used in Chapter 6 can be modified to represent cross-product interactions as depicted in Figure 7.1.

Technology (Tool Function)

Task (User Need)

	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	1 FIT	2 FIT	3 FIT	4 FIT
Interdependence	5 FIT	6 FIT	7 FIT	8 FIT
Mobility	9 FIT	10 FIT	11 FIT	12 FIT
Information Dependency	13 FIT	14 FIT	15 FIT	16 FIT

Figure 7.1. Task-Technology Fit (TTF) Matrix: Configured Cross-Product Terms

The TTF matrix in Figure 7.1 shows that there are sixteen possible ways in which CHW task characteristics and mHealth tool characteristics can interact. The shaded cells represent these interactions. Venkatraman (1989) originally specified the Fit as Moderation perspective with reference to a criterion (p. 424). Therefore, the effect of TTF on the criteria variables of use and user performance can be examined.

The link between TTF as Moderation and use and user performance is discussed in Section 7.2.

7.3 Conceptual Model

7.3.1 The Link between Task-Technology Fit (TTF) as Moderation and Use and User Performance

Fit as the cross-product interaction of task and technology characteristics, impacts use and user performance (Teo and Men, 2008). The link between TTF as Moderation and use and user performance is shown in Figure 7.2.

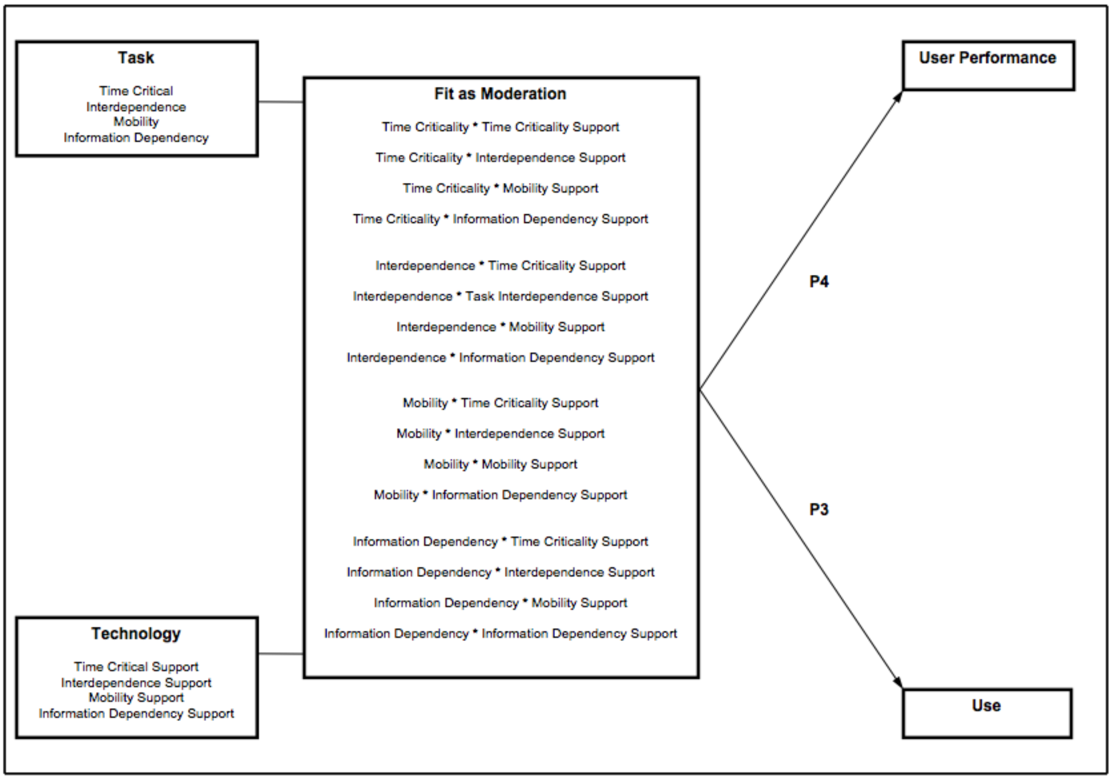

Figure 7.2. The Link between Task-Technology Fit (TTF) as Moderation and Use and User Performance

If the technology used interacts with the task performed, then use and user performance should improve. Task (user need) characteristics would have a stronger effect on use and user performance at higher functional support levels, but a weaker effect at lower functional support levels. In essence, the strength of the relationship between task characteristics and use and user performance would vary due to differences in technology characteristics of the tool. Therefore the task requirement would determine user behaviour, depending on levels of functional support (Teo and Men, 2008, p. 563). In their TTF study, Teo and Men (2008) hypothesized that when differences in technology characteristics such as output quality are observed, usage behaviour may not be the same even if the task characteristics of users are similar (p. 563). Thus the importance of technology characteristics as a moderator is recognized. Essentially, mHealth tool functions would moderate the relationship between CHW needs, and use and user performance. Consequently, CHW task characteristics would have a stronger effect on use and user performance at higher functional support levels. In prior works, hypotheses premised upon technology characteristics moderating the relationships between task characteristics, and use and user performance, have been formulated (Strong, Dishaw and Bandy, 2006; Teo and Men, 2008). To examine the link between TTF as Moderation and use and user performance, the following propositions are formulated:

Proposition 3 (P3): *Fit as the cross-product interaction of all CHW task characteristics and all mHealth tool characteristics will influence use.*
Proposition 4 (P4): *Fit as the cross-product interaction of all CHW task characteristics and all mHealth tool characteristics will influence user performance.*

The methods used to examine the impact of TTF as Moderation on use and user performance, are discussed in Section 7.4.

7.4 Methods

7.4.1 Sampling, Instrument and Measures

Dataset 1 (n = 201) is used in this chapter. Dataset 1 is described in detail in Section B.1 of Appendix B. The dataset consists of responses from CHW mHealth tool users in the counties of Siaya, Nandi, and Kilifi. A structured questionnaire survey instrument was used to collect the data. The measures for CHW task characteristics, mHealth technology characteristics, use and user performance, were developed as described in Appendix E. These constructs were tested for multi-collinearity, reliability and validity, and final measures were used in subsequent analyses as per the procedures and criteria outlined in in Sections G.1 and G.2 of Appendix G.

7.4.2 Task-Technology Fit (TTF) as Moderation

As indicated in Section 7.2, the Fit as Moderation (Venkatraman, 1989) perspective has been adopted to operationalize interacting task and technology characteristics as a cross-product (Teo and Men, 2008).

In this study, TTF as Moderation is operationalized as the cross-product of interacting CHW task and mHealth tool characteristics. These interaction terms can then be examined for their effects on use and user performance. The interaction between these characteristics was computed using equation 1:

$$\text{Fit}^{\text{INTERACT } IJ} = \text{Task Characteristic } I \times \text{Technology Characteristic } J \qquad (1)$$

where:

$\text{Fit}^{\text{INTERACT } IJ}$ = Task-Technology Fit (TTF) of mHealth technology characteristic J to CHW task characteristic J

I = Supporting Technology Characteristic (Tool Function)

J = Task Characteristics (User Need)

Using equation 1, the sixteen possible interactions of CHW task and mHealth tool characteristics were computed as interaction terms (Henseler and Fassott, 2010, p. 723). The modified TTF matrix depicted in Figure 7.3 captures each interacting task and technology characteristic as a cross-product term in the cells numbered from 1 to 16.

Technology (Tool Functions)

Task (User Needs)

	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	1 T x TCS FIT	2 TC x IS FIT	3 TC x MS FIT	4 TC x IDS FIT
Interdependence	5 I x TCS FIT	6 I X IS FIT	7 I X MS FIT	8 I x IDS FIT
Mobility	9 M x TCS FIT	10 M X IS FIT	11 M x MS FIT	12 M x IDS FIT
Information Dependency	13 ID x TCS FIT	14 ID x IS FIT	15 ID x MS FIT	16 ID x IDS FIT

Figure 7.3. Task-Technology Fit (TTF) Matrix: Computed Interaction

Dishaw (1994) argued that a primary, on-diagonal, 'fit' of corresponding (matching) task and technology characteristics is expected, but conceded that a secondary, off-diagonal, 'fit' of tool functionality to user activities could and must occur (p. 119). In essence, a tool function designed for a specific user need can instead fit another, secondary task requirement (Dishaw, 1994, p. 37). Thus in this chapter, greater emphasis is placed on examining these secondary (off-diagonal) fit interactions[44] of CHW task and mHealth tool characteristics. It is, however, important to recognize that as per Figure 7.3, cross-product interactions encompass both interacting primary (on-diagonal) and secondary (off-diagonal) task and technology characteristics. Notably, secondary (off-diagonal) fit interactions are typically considered an exception (Dishaw, 1994). As such, a selective approach is employed to identify and examine only those significant off-diagonal, interaction TTF effects on use and user performance.

In accordance with equation 1 and Figure 7.3, continuous moderating effects were modelled using a product indicator approach to create cross-product interaction terms for use in PLS-SEM testing (Hair et al., 2014 p. 263). The indicator values expressed in Equation 1 were mean-centered prior to multiplication. As observed in Chapter 6, this was necessary because centering predictor variables greatly lessens multi-collinearity when using multiplicative terms to model moderating effects (Henseler and Fassott, 2010, p. 728).

A structural path model was then estimated to examine the effects of each cross-product interaction on use and user performance. Interaction effects on use and user performance were graphically plotted for significant cross-product terms. A structural path model was also estimated to examine the combined effects of all cross-product interactions on use and user performance. Coefficients of determination (R^2 values) of the endogenous constructs use and user performance were used to determine the predictive accuracy[45] of the estimated PLS structural path models (Hair et al., 2014, p. 174), and Stone-Geisser's Q^2 values (Geisser, 1974; Stone, 1974) of use and user performance were used to determine their predictive relevance[46] (Hair et al., 2014, p. 178). In addition, f^2 (q^2) effect sizes[47] were computed to determine the relative impacts of significant interacting pairs of task and technology characteristics, on the predictive accuracy (R^2) and relevance (Q^2) of the PLS structural path models estimated to examine the effects of each cross-

[44] Refer Chapter 6 for analyses of primary (on-diagonal) fit (matching) of CHW task and mHealth tool characteristics.
[45] R^2 values of approximately 0.670, 0.333, and 0.190 are substantial, moderate, and weak, respectively (Chin, 1998; Urbach and Ahlemann, 2010, p. 21).
[46] Q^2 values larger than zero for a certain reflective endogenous latent variable are indicators of predictive relevance (Henseler et al., 2009, Hair et al., 2014, p. 178).
[47] For f^2, values of 0.02, 0.15, and 0.35 are small, medium, and large effects, respectively (Cohen, 1988). These threshold values are also used to assess q^2 (Urbach and Ahlemann, 2010; Hair et al., 2014).

product interaction on use and user performance (Urbach and Ahlemann, 2010; Hair et al., 2014).

To extend and enrich the Moderation interaction 'fit' perspective (Venkatraman, 1989, p. 438), TTF was examined for non-linear interaction effects on use and user performance using Polynomial Regression with Response Surface Methodology (Edwards, 1993, 2002; Shanock et al., 2010; Yang et al., 2013). This technique is used for a more nuanced view of the relationships between bi-variate combinations of predictors and a criterion, by graphing the results of polynomial regression analyses in a three-dimensional (3-D) plane (Edwards and Parry, 1993). In this chapter, 'fit' is a bi-variate product of task and technology components. Thus the dynamic, multiple, non-linear interaction effects of 'fit' at varying levels of task need and technology functionality can be precisely captured (Yang et al., 2013, p. 699).

Results of the structural path model estimates of TTF as Moderation (Interaction) are discussed in Section 7.5.

7.5 Results

7.5.1 Cross-Product Interaction (Cells 1 to 4)

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path models estimated to test the interactions in cells 1 to 4 (Figure 7.3), by evaluating the moderating effects of mHealth technology characteristics on the relationship between t*ime criticality* in CHW tasks, and *use* and *user performance*, are shown in Table 7.1.

Table 7.1. Structural Path Model Results: Cross-Product Interactions (Cells 1 - 4)						
Cell[48]	Interaction Effect	Path Coefficient	*t*	*p*	Significance	90% CI
1	*Time Criticality x Time Criticality Support (TC * MS) → Use*	0.103	1.49	0.14	NS	[-0.01, 0.22]
	*Time Criticality x Time Criticality Support (TC * MS) → User Performance*	0.176	2.23	0.03	**	[0.05, 0.31]
	R^2 = 0.219, f^2 *(TC * TCS) → User Performance* = 0.04, Q^2 = 0.135, q^2 *(TC * TCS) → User Performance* = 0.02					
2	*Time Criticality x Interdependence Support → (TC * IS) Use*	0.181	0.93	0.35	NS	[-0.14, 0.50]
	*Time Criticality x Interdependence Support → (TC * IS) User Performance*	-0.108	0.52	0.61	NS	[-0.45, 0.24]
3	*Time Criticality x Mobility Support (TC * MS) → Use*	-0.210	1.12	0.27	NS	[-0.52, 0.10]
	*Time Criticality x Mobility Support (TC * MS) → User Performance*	-0.258	1.16	0.25	NS	[-0.62, 0.11]
4	*Time Criticality x Information Dependence Support → (TC * IDS) Use*	-0.213	1.06	0.29	NS	[-0.54, 0.12]
	*Time Criticality x Information Dependence Support → (TC * IDS) User Performance*	-0.122	0.63	0.53	NS	[-0.44, 0.19]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 7.1 indicate that the moderating effect of *time criticality tool support* on the links between *time criticality* of tasks and *user performance* is positive and significant (path coefficient = 0.176, t = 2.23, p < 0.05). This is an affirmation of the on-diagonal or matching[49] effect. However, there were no significant off-diagonal effects, such that the tool functions of *interdependence support*, *mobility support*, and *information dependency support*, did not moderate the effects of time criticality on CHW performance. None of the cross-product interactions were significant for mHealth tool use. ***Proposition 3 (P3)*** and ***Proposition 4 (P4)*** are not supported for time criticality.

7.5.2 Cross-Product Interaction (Cells 5 to 8)

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path models estimated to test the interactions in cells 5 to 8 (Figure 7.3), by evaluating the moderating effects of mHealth technology characteristics on the

[48] Each cell in TTF matrix (Figure 7.3) is examined by rows representing four support functions for a particular need.
[49] Refer Chapter 6 for discussions of TTF as Matching.

relationship between *interdependence* in CHW tasks and *use* and *user performance*, are shown in Table 7.2.

Table 7.2. Structural Path Model Results: Cross-Product Interaction (Cells 5 - 8)						
Cell	Interaction Effect	Path Coefficient	*t*	*p*	Sig Level	90% CI
5	*Interdependence x Time Criticality Support (I * TCS) → Use*	-0.099	1.06	0.29	NS	[-0.43, 0.23]
	*Interdependence x Time Criticality Support (I * TCS) → User Performance*	0.200	0.64	0.53	NS	[-0.12, 0.51]
6	*Interdependence x Interdependence Support (I * IS) → Use*	-0.104	1.47	0.14	NS	[-0.22, 0.01]
	*Interdependence x Interdependence Support (I * IS) → User Performance*	0.102	1.33	0.19	NS	[-0.02, 0.23]
7	*Interdependence x Mobility Support (I * MS) → Use*	0.179	1.06	0.29	NS	[-0.15, 0.51]
	*Interdependence x Mobility Support (I * MS) → User Performance*	0.207	0.64	0.53	NS	[-0.11, 0.52]
8	*Interdependence x Information Dependence Support (I * IDS) → Use*	-0.093	1.06	0.29	NS	[-0.42, 0.24]
	*Interdependence x Information Dependence Support (I * IDS) → User Performance*	0.171	0.64	0.53	NS	[-0.14, 0.49]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 7.2 indicate that there were no significant on-diagonal or off-diagonal fit effects. ***Proposition 3 (P3)*** and ***Proposition 4 (P4)*** are not supported for interdependence.

7.5.3 Cross-Product Interaction (Cells 9 to 12)

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path models estimated to test the interactions in cells 9 to 12 (Figure 7.3), by evaluating the moderating effects of mHealth technology characteristics on the relationship between *mobility* in CHW tasks and *use* and *user performance*, are shown in Table 7.3.

Table 7.3. Structural Path Model Results: Cross-Product Interaction (Cells 9 - 12)

Cell	Interaction Effect	Path Coefficient	*t*	*p*	Sig Level	90% CI
9	*Mobility x Time Criticality Support (M * TCS) → Use*	-0.285	0.24	0.81	NS	[-0.67, 0.10]
	*Mobility x Time Criticality Support (M * TCS) → User Performance*	-0.266	0.16	0.87	NS	[-0.53, 0.00]
10	*Mobility x Interdependence Support (M * IS) → Use*	-0.311	1.65	0.10	**	[-0.62, -0.00]
	R^2 = 0.253, f^2 *(M * IS)→ Use* = 0.10, Q^2 = 0.074, q^2 *(M * IS) → Use* = 0.05					
	*Mobility x Interdependence Support (M * IS) → User Performance*	-0.279	1.65	0.05	*	[-0.51, -0.05]
	R^2 = 0.195, f^2 *(M * IS)→ User Performance* = 0.10, Q^2 = 0.125, q^2 *(M * IS) → User Performance* = 0.05					
11	*Mobility x Mobility Support (M * MS) → Use*	-0.315	4.71	0.00	***	[-0.42, -0.21]
	R^2 = 0.164, f^2 *(M * MS) → Use* = 0.11, Q^2 = 0.097, q^2 *(M * MS)→ Use* = 0.07					
	*Mobility x Mobility Support (M * MS) → User Performance*	-0.350	4.17	0.00	***	[-0.49, -0.21]
	R^2 = 0.323, f^2 *(M * MS) → User Performance* = 0.17, Q^2 = 0.193, q^2 *(M * MS)→ User Performance* = 0.08					
12	*Mobility x Information Dependency Support (M * IDS) → Use*	-0.186	1.20	0.23	NS	[-0.44, 0.07]
	*Mobility x Information Dependency Support (M * IDS)→ User Performance*	-0.360	2.29	0.02	**	[-0.62, -0.10]
	R^2 = 0.251, f^2 *(M * IDS) → user performance* = 0.17, Q^2 = 0.156, q^2 *(M * IDS) → user performance* = 0.10					

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 7.3 indicate that in addition to the negative on-diagonal effects observed, two off-diagonal interactions were significant for CHW performance, and one off-diagonal interaction was significant for use. The first significant off-diagonal interaction finding was that *interdependence support* moderates the effect of *mobility* in tasks on *use* (path coefficient = -0.311, *t* = 1.65, p < 0.10) and *user performance* (path coefficient = -0.279, *t* = 1.65, p < 0.10). These moderating effects are however not consistent with ***Proposition 3 (P3)*** and ***Proposition 4 (P4)***, as they are not in the expected direction.

The structural path model estimated to test TTF moderation effects of interacting *mobility* and *interdependence support* is depicted in Figure 7.4.

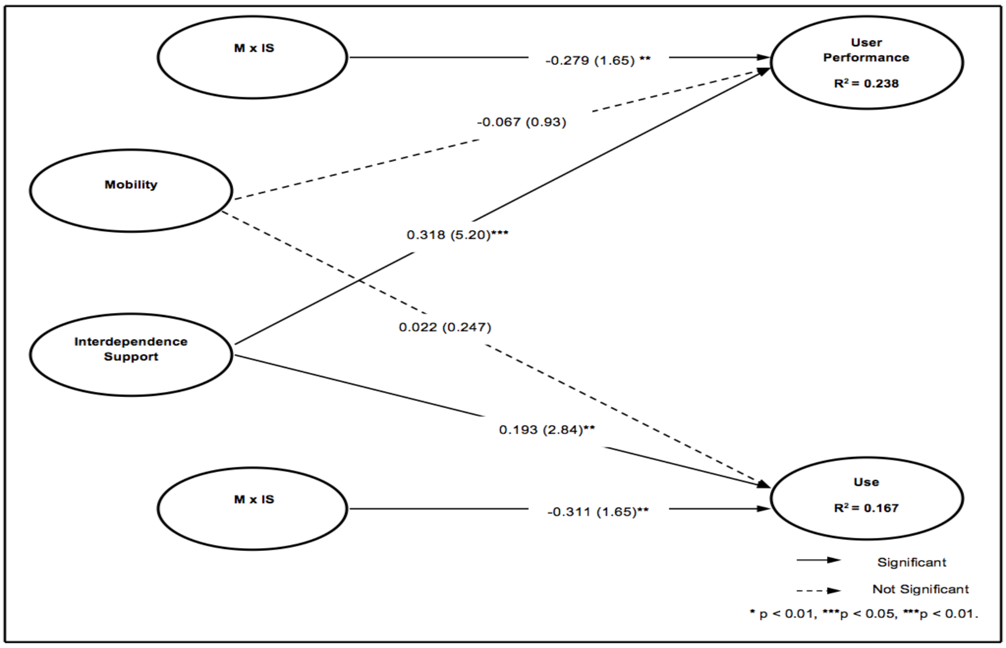

Figure 7.4. Path Model: Mobility Interdependence Support Fit

The moderating effect of the technology's interdependence support on the links between mobility task characteristics and tool use, and CHW performance is illustrated in Figures 7.5 and 7.6.

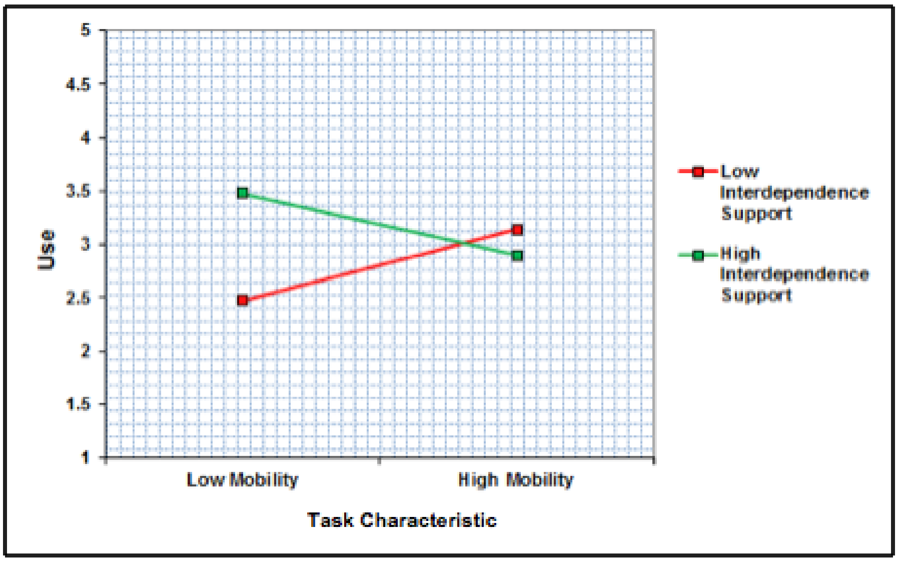

Figure 7.5. Mobility Interdependence Support Fit: Interaction Effects on Use

Figure 7.5 shows that the effect of mobility of tasks on the use of the tool depends on whether the tool has functionality that integrates data from others. It shows that mobility of tasks increases use of the tool when functionality is low, but decreases use when functionality is high.

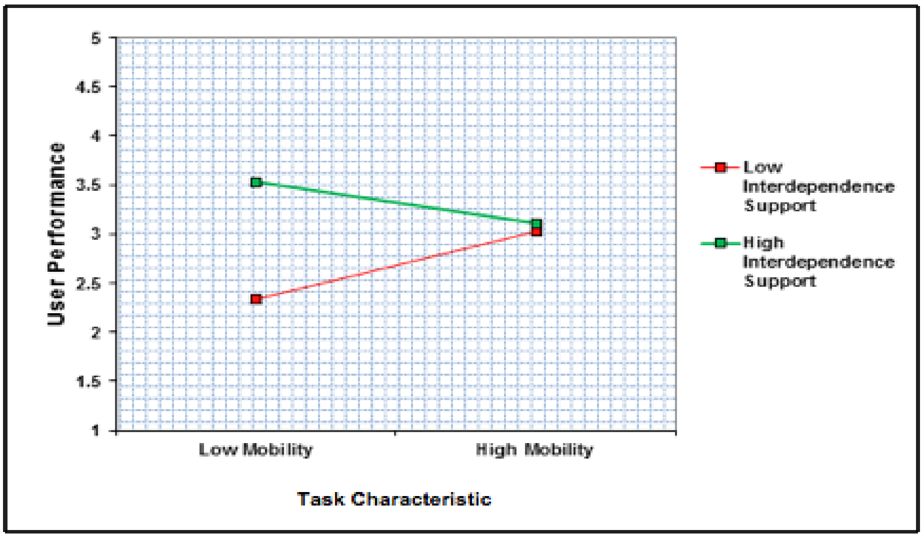

Figure 7.6. Mobility Interdependence Support Fit: Interaction Effects on User Performance

Similarly, Figure 7.6 shows that as the mobility of tasks increases, performance will decrease with a tool with high support for data integration, but increase with a tool with low support for data integration. When a CHW moves a short distance from location to location, they are less likely to depend on the use of the mHealth tool unless they have a high need to access integrated data functionality of the tool. However, it is very difficult to improve the performance of CHWs who move a lot from location to location, as their use of the tool and their performance does not depend as much on whether it has data integration capabilities.

The second significant off-diagonal interaction was that *information dependency support* of the tool moderates the effect of *mobility* in task characteristics on *user performance* (path coefficient = -0.360, t = 2.29, $p < 0.05$). However, this moderating effect is not consistent with ***Proposition 4 (P4)*** since it is not in the expected direction.

The structural path model estimated to test TTF moderation effects of interacting *mobility* and *information dependency support* is depicted in Figure 7.7. The moderating effect is illustrated in Figure 7.8.

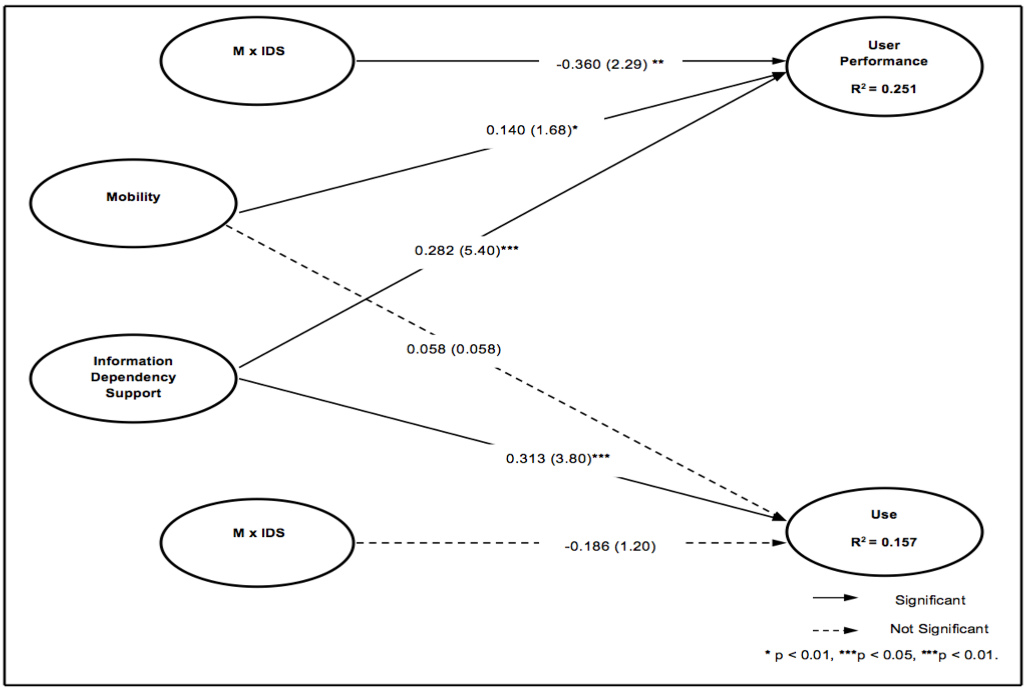

Figure 7.7. Path Model: Mobility Information Dependency Support Fit

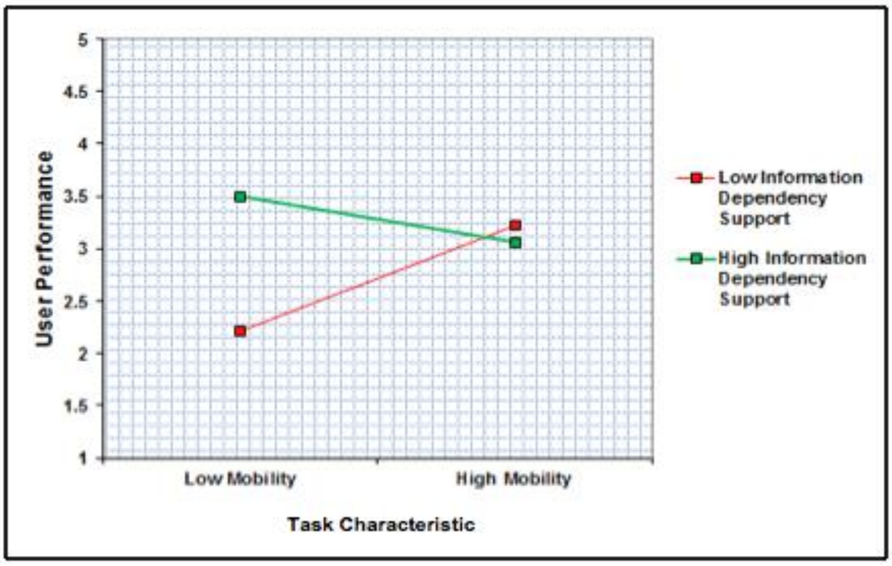

Figure 7.8. Mobility Information Dependency Support Fit: Interaction Effects on User Performance

In Figure 7.8, a similar pattern exists where, as the mobility of tasks increases, performance will decrease with a tool with high support for information provision, but increase with a tool with low support for data provision. The performance of CHWs who move a lot from location to location does not depend on whether the mHealth tool has data provision capabilities.

The final significant interaction was an on-diagonal interaction of *mobility* with *mobility support*, in relation to *use* (path coefficient = -0.315, t = 4.71, $p < 0.01$). This on-diagonal interaction was discussed in Chapter 6.

7.5.4 Cross-Product Interaction (Cells 9 to 12)

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path models estimated to test the interactions in cells 13 to 16 (Figure 7.3), by evaluating the moderating effects of mHealth technology characteristics on the relationship between *information dependency* in CHW tasks and *use* and *user performance*, are shown in Table 7.4.

Table 7.4. Structural Path Model Results: Cross-Product Interaction (Cells 13 - 16)

Cell	Interaction Effect	Path Coefficient	*t*	*p*	Sig Level	90% CI
13	*Information Dependency x Time Criticality Support (ID * TCS) → Use*	-0.057	0.40	0.69	NS	[-0.29, 0.18]
	*Information Dependency x Time Criticality Support (ID * TCS) → User Performance*	0.271	1.90	0.06	**	[0.04, 0.50]
	R^2 = 0.208, f^2 *(ID * TCS) → user performance* = 0.09, Q^2 = 0.134, q^2 *(ID * TCS) → user performance* = 0.06					
14	*Information Dependency x Interdependence Support (ID * IS) → Use*	-0.145	1.18	0.24	NS	[-0.35, 0.06]
	*Information Dependency x Interdependence Support (ID * IS) → User Performance*	-0.180	0.69	0.49	NS	[-0.61, 0.25]
15	*Information Dependency x Mobility Support (ID * MS) → Use*	-0.084	0.51	0.61	NS	[-0.35, 0.19]
	*Information Dependency x Mobility Support (ID * MS) → User Performance*	-0.107	0.51	0.61	NS	[-0.45, 0.23]
16	*Information Dependency x Information Dependency Support (ID * IDS) → Use*	-0.141	1.74	0.08	*	[-0.27, -0.01]
	R^2 = 0.188, f^2 *(ID * IDS) → Use* = 0.03, Q^2 = 0.095, q^2 *(ID * IDS) → Use* = 0.02					
	*Information Dependency x Information Dependency Support (ID * IDS) → User Performance*	0.253	2.80	0.01	**	[0.11, 0.40]
	R^2 = 0.189, f^2 *(ID * IDS) → User Performance* = 0.07, Q^2 = 0.117, q^2 *(ID * IDS) → User Performance* = 0.04					

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

The significant but negative on-diagonal interaction between information dependency and information dependency support was previously discussed in Chapter 6.

Results in Table 7.4 indicate that only one off-diagonal interaction was significant, between *information dependency* of tasks and *time criticality support of the mHealth* tool, in relation to *user performance* (path coefficient = 0.271, t = 1.90, p < 0.10). Thus ***Proposition 4 (P4)*** was partially supported for information dependency.

The structural path model estimated to test TTF moderation effects of interacting *information dependency* and *time criticality support* is depicted in Figure 7.9.

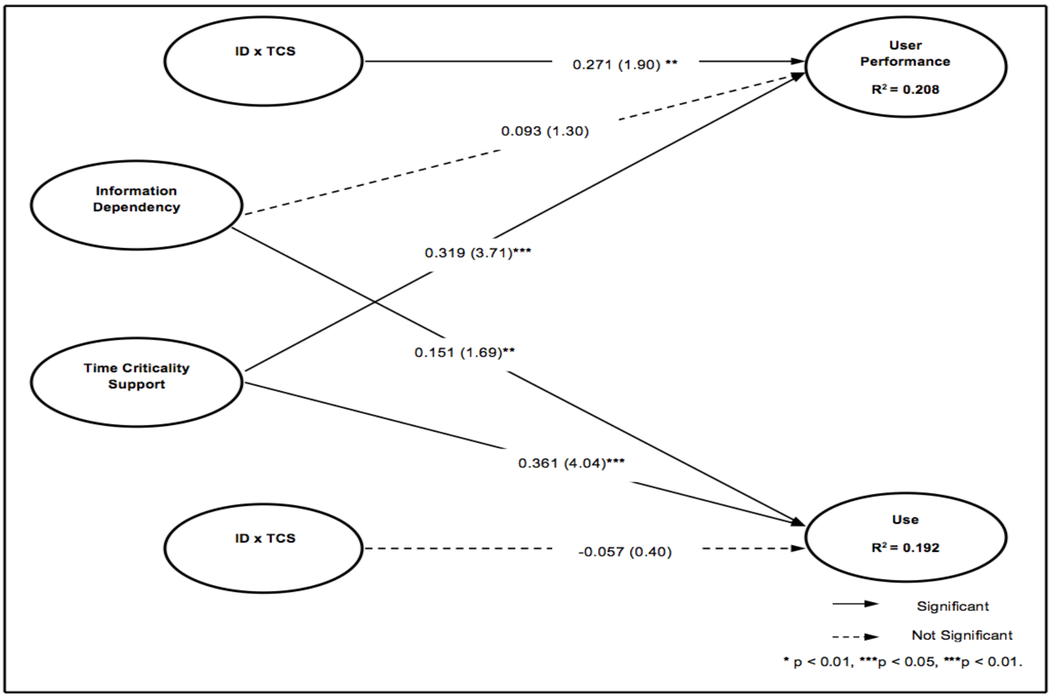

Figure 7.9. Path Model Information Dependency Time Criticality Support Fit

Figure 7.10 shows the moderating effect of *time criticality support* on the link between *information dependency* of tasks and mHealth *use* and *CHW performance*.

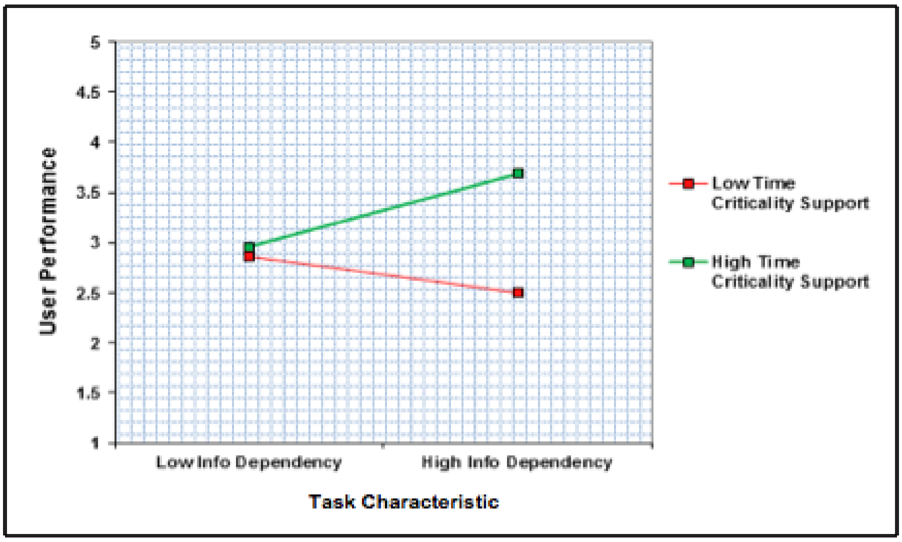

Figure 7.10. Information Dependency Time Criticality Support Fit: Interaction Effects on User Performance

Figure 7.10 shows that the effect of information dependency of tasks on the performance of the user depends on whether the tool has functionality that enables time-critical responsiveness. When information dependency is high, performance increases with time criticality support but decreases with lack of support. This is likely because users who need access to information to complete their tasks are likely to perform better when that information is provided quickly.

7.5.5 Combined Cross-Product Interaction

The combined effect of all sixteen TTF cross-product interactions of CHW task (need) and mHealth tool (function) characteristics on *use* and *user performance* was tested. This structural path model has significant predictive accuracy for the endogenous constructs *use* (R^2 = 0.412) and *user performance* (R^2 = 0.614). The model has significant predictive relevance for the endogenous constructs *use* (Q^2 = 0.214) and *user performance* (Q^2 = 0.385). The direct and moderating effects obtained for the endogenous constructs *use* and *user performance*, are summarized in Table 7.5.

Table 7.5. Results: Combined Moderation (Interaction) Effects		
Predictor	**Criterion**	
	Use	**User Performance**
	Effect (+/-)	**Effect (+/-)**
Task Characteristics		
Time Criticality	NS	NS
Interdependence	NS	NS
Mobility	NS	NS
Information Dependency	NS	NS
Technology Characteristics		
Time Criticality Support	NS	(+) MAIN
Interdependence Support	NS	(+) MAIN
Mobility Support	NS	(+) MAIN
Information Dependency Support	(+) MAIN	NS
Interactions		
*1. Time Criticality x Time Criticality Support (TC * MS)*	NS	NS
*2. Time Criticality x Interdependence Support (TC * IS)*	NS	NS
*3. Time Criticality x Mobility Support (TC * MS)*	NS	NS
*4. Time Criticality x Information Dependence Support (TC * IDS)*	NS	NS
*5. Interdependence x Time Criticality Support (I * TCS)*	NS	NS
*6. Interdependence x Interdependence Support (I * IS)*	NS	NS
*7. Interdependence x Mobility Support (I * MS)*	NS	NS
*8. Interdependence x Information Dependence Support (I * MS)*	NS	NS
*9. Mobility x Time Criticality Support (M * TCS)*	NS	NS
*10. Mobility x Interdependence Support (M * IS)*	NS	NS
*11. Mobility x Mobility Support (M * MS)*	NS	NS
*12. Mobility x Information Dependency Support (M * IDS)*	NS	NS
*13. Information Dependency x Time Criticality Support (ID * TCS)*	NS	NS
*14. Information Dependency x Interdependence Support (ID * IS)*	NS	NS
*15. Information Dependency x Mobility Support (ID * IS)*	NS	NS
*16. Information Dependency x Information Dependency Support (ID * IDS)*	NS	NS
Predictive Significance of Model		
R-squared (R^2)	0.412 (+)	0.614 (+)
Q-squared (Q^2)	0.214 (+)	0.385 (+)

NS = Non-Significant Effect, MAIN = Main Effect,

(+) = Positive Significant Effect, (-) = Negative Significant Effect,

R^2 = Model Predictive Accuracy, Q^2 = Model Predictive Relevance

Table 7.5 indicates that the mHealth tool characteristic *information dependency support* is significant for *use*. In addition, the mHealth tool characteristics *time criticality support*, *interdependence support*, and *mobility support*, are significant for *user performance*. However, none of the sixteen cross-product interactions signifying support for the CHW task characteristics *time criticality support*, *interdependence support*, *mobility support*, and *information dependency support*, appear to be significant for *use* and *user performance*. This could be due to the multiplicity of shared dependencies between task and technology characteristics, such that independent main and interaction effects are diminished in a combined effects model. In essence, it must be recognized that many user tasks can be dependent on one technology characteristic, or one task can be dependent on many technology characteristics. In contrast, results in Chapter 6 indicated that matching interactions have identical effects on use and user performance in both the independent and simultaneous TTF structural path models that were estimated. Therefore, unlike Moderation interaction, Matching appears to exhibit uniform characteristics whether independently or within a combined effects TTF structural path model. Notably, as independent main and interaction effects appear to be negated, the overall predictive explanatory power of the TTF as Moderation (interaction) combined effects model appears to be significant. This interplay between effects and overall predictive model significance would nevertheless warrant further investigation. Results of tests of TTF as Moderation (Interaction) on use and user performance are summarized in Table 7.6.

Table 7.6. Findings		
Proposition		Finding
P3	Fit as the cross-product interaction of CHW need and mHealth tool characteristics, will influence use.	• Mobility Interdependence Support Fit as Moderation (Interaction) negatively influences use.
P4	Fit as the cross-product interaction of CHW need and mHealth tool characteristics, will influence user performance.	• Mobility Interdependence Support Fit as Moderation (Interaction) negatively influences user performance. • Mobility Information Dependency Support Fit as Moderation (Interaction) negatively influences user performance. • Information Dependency Time Criticality Support Fit as Moderation (Interaction) positively influences user performance.

As articulated in Section 7.4, TTF as Moderation (interaction) can be further examined for non-linear effects on use and user performance (Edwards and Parry, 1993). The linear relationship between TTF interaction and use and user performance is often presumed in prior works (Yang et al., 2013). Moreover, TTF interaction has often been viewed as a single, stable, static point. However, as evidenced by recent research, the relationship between TTF, and use and user performance, can be represented as multiple states of equilibrium that differ in terms of their magnitude and location (Yang et al., 2013, p. 696). Therefore a more nuanced TTF interaction perspective is observable. Thus TTF must be examined for non-linear interaction effects on use and user performance. This examination of non-linear interaction TTF effects is discussed next.

7.5.6 The Non-Linear Effect of Task Technology Fit (TTF) as an Interaction, on Use and User Performance

In this section, the use of Polynomial Regression with Response Surface Methodology (Edwards, 1993, 2002; Shanock et al., 2010; Yang et al., 2013) to examine the interaction of task and technology components for non-linear effects on use and user performance is described. These non-linear TTF effects are examined using an atomistic approach, which involves testing the task and technology components separately in order to assess the impact of each factor on use and user performance (Edwards, 1991; Oh and Pinsonneault, 2007). Furthermore, this approach is used to observe the impact of TTF in relation to dynamic changes in equilibrium levels between functional support and user needs (Yang et al., 2013, p. 704). The use of Response Surface Methodology (RSM) ensures that the value of each component (task and technology) is preserved, as the extent of 'fit' is computed without collapsing these components into one construct. This is aligned with the purpose of the atomistic approach, to evaluate a 'fit' between two predictors and its impacts (Yang et al., 2013). To examine 'fit' using the atomistic approach, PLS-SEM was used to estimate a reflective formative Type II model (Becker, Klein and Wetzels, 2012, p. 363) to obtain unstandardized latent variable scores used as scale measures[50] for purposes of Polynomial Regression[51]. For this type of model[52], the task and technology are second-order factors with underlying characteristics as first-order factors. These first-order factors are themselves formative indicators of the second-order factors (Jarvis, Mackenzie and Podsakoff, 2013). As discussed in Section 7.4.2, a PLS-SEM product indicator approach was used to compute TTF interaction terms and model continuous moderator effects on use and user performance (Henseler and Fassott, 2010; Hair et al., 2014). Similarly, in prior works, methods used to examine TTF have included standard multiple and Partial Least Squares (PLS) regressions, and factor analysis. Moreover, in many of these works, TTF has been directly measured as a user-perceived construct, and in limited studies, as an aggregation of two component factors into a composite index (Yang et al., 2013). In contrast, Polynomial Regression (Edwards, 1993) can be used to model the relationship between task and technology characteristics and use and user performance, as a non-linear function (Yang et al., 2013, p. 706). This technique can have

[50] Please refer Section M.1 of Appendix M for a discussion of scale measurement parameters.
[51] Please refer Section M.1 of Appendix M for a discussion of Polynomial Regression.
[52] This structural model and its path effects are presented with further details in Figure M.1 of Appendix M.

greater explanatory potential than conventional moderated regression analyses. Furthermore, it can be used as an alternative to moderated regression, as it outputs more precise information on combinations (interactions) of variables, beyond the results of the more conventional moderator analyses (Shanock et al., 2010).

The latent variable scores obtained from PLS-SEM analysis were used to compute task (X) and technology (Y) components, their interaction (XY), and quadratic terms (X^2, Y^2), for predicting use and user performance using Polynomial Regression as per the following expression:

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e$$

where:

Z = Use or User Performance

X = The Task

Y = The Technology

The above variables were centered at their midpoints i.e. '4' for seven point Likert scales. Centering is recommended for Polynomial Regression Analyses (Edwards, 1994). Moreover, Aiken and West (1991) suggested that centering minimizes the likelihood of multicollinearity. Using the above equation, beta (β) coefficients for the terms X (b_1), Y (b_2), X^2 (b_3), XY (b_4) and Y^2 (b_5) were obtained. Results of the Polynomial Regression are summarized in Table 7.7.

Table 7.7. Polynomial Regression Results: Task-Technology Fit (TTF) Impacts

Use			User Performance		
Predictor	**Beta (β)**	**Standard Error**	**Predictor**	**Beta (β)**	**Standard Error**
Constant (b_0)	4.470***	0.231	Constant (b_0)	5.370***	1.149
Task (b_1X)	0.073	0.183	Task (b_1X)	0.124	1.118
Technology (b_2Y)	0.758***	0.214	Technology (b_2Y)	0.369*	1.138
Task^2 (b_3X^2)	0.061	0.084	Task^2 (b_3X^2)	-0.045	0.540
Task*Technology (b_4XY)	-0.053	0.097	Task*Technology (b_4XY)	0.091	0.063
Technology^2 (b_5Y^2)	-0.070	0.060	Technology^2 (b_5Y^2)	-0.039	0.039
R^2 = 0.202, F = 9.872***			R^2 = 0.300, F = 16.703***		

******* $p < 0.0001$, ****** $p < 0.01$, ***** $p < 0.05$

Using Response Surface Methodology, three-dimensional (3-D) surfaces of the TTF, use and user performance components were plotted (Edwards, 2002 p. 376). Regression beta (β) coefficients obtained using equation 9, were used to estimate stationary points (X_0, Y_0), first (p_{10}, p_{11}) and second (p_{20}, p_{21}) principal axes, as well as lines of congruence (a_3, a_4) and incongruence (a_1, a_2). The response surface values[53] obtained to examine TTF for non-linear effects on use and user performance are shown in Table 7.8.

Table 7.8. Response Surface Analysis Results: Task-Technology Fit (TTF)					
Use			User Performance		
Stationary Point	X_0	1.506 (0.011)	**Stationary Point**	X_0	-34.299 (-0.339)
	Y_0	4.844 (0.045)		Y_0	-35.285 (-0.376)
First Principal Axis	Intercept (P_{10})	5.137 (0.013)	**First Principal Axis**	Intercept (P_{10})	1.350 (0.002)
	Slope (P_{11})	-0.195 (-0.001)		Slope (P_{11})	1.068 (0.006)
	($-P_{10}/(1+P_{11})$	-6.379 (-0.003)		($-P_{10}/(1+P_{11})$	-0.653 (0.000)
Second Principal Axis	Intercept (P_{20})	-2.894 (-0.002)	**Second Principal Axis**	Intercept (P_{20})	-67.397 (-0.056)
	Slope (P_{21})	5.138 (0.015)		Slope (P_{21})	-0.936 (-0.009)
Shape Along Line of Congruence (Y = X)	Slope: a_1 ($b_1 + b_2$)	0.831 (2.797) ***	**Shape Along Line of Congruence (Y = X)**	Slope: a_1 ($b_1 + b_2$)	0.493 (1.394)
	Curvature: a_2 ($b_3 + b_4 + b_5$)	-0.062 (-0.595)		Curvature: a_2 ($b_3 + b_4 + b_5$)	0.007 (0.068)
Shape Along Line of Incongruence (Y = -X)	Slope: a_3 ($b_1 - b_2$)	-0.685 (-1.505)	**Shape Along Line of Incongruence (Y = -X)**	Slope: a_3 ($b_1 - b_2$)	-0.245 (-0.616)
	Curvature: a_4 ($b_3 - b_4 + b_5$)	0.044 (0.139)		Curvature: a_4 ($b_3 - b_4 + b_5$)	-0.175 (-0.569)

*p < 0.10. **p < 0.05. ***p < 0.01.

The response surface for the task (X) and technology (Y) predicting *use* (Z) is shown in Figures 7.11 (a) and (b).

[53] The slopes and curvatures along lines of congruence (Y = X) and incongruence (Y = - X) represent surface responses.

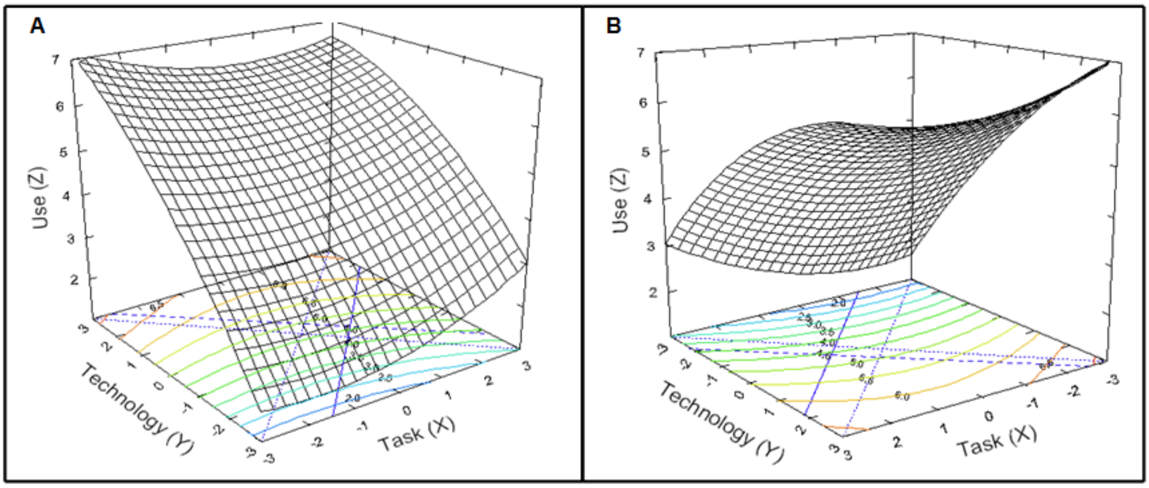

Figure 7.11. Response Surface: Task-Technology Fit (TTF) Effects on Use: Front (a) and Rear (b)

The response surface for TTF effects on use was concave shaped[54] (stationary point: X_0 = 1.506, Y_0 = 4.844). The first principal axis is not significantly different [t = -0.001 (p_{11}), t = -0.003 ($-p_{10}/p_{11}+1$)] from the line of congruence (Y = X)[55]. As such, a perfect fit between the task and technology leads to maximal use. The upward slope along the line of congruence (Y = X) is positive and significant (a_1 = 0.831, *t* = 2.797, p < 0.01). A closer fit between the CHW task and the mHealth tool leads to an increase in use. Consequently, when the CHW task and mHealth tool fit (are congruent), user needs and functional support levels increase with increasing levels of technology dependence. The curvature[56] along the line of congruence (Y = X)[57] was negative but not significant (a_2 = -0.062, *t* = -0.595), indicating that the relationship between TTF and use is linear. This indicates that the curvature along line Y = X does not significantly change for mHealth tool use. The downward slope along the line of incongruence (Y = -X) was negative but not significant (a_3 = -0.685, *t* = -1.505). A lack of fit between the task and technology leads to a decrease in use. The curvature along the line of incongruence (Y = -X) was positive but non-significant (a_4 = 0.044, *t* = 0.139), further indicating that the relationship between TTF and use is linear.

The response surface for the task (X) and technology characteristics (Y) predicting *user performance* (Z) is shown in Figures 7.12 (a) and (b).

[54] For a concave surface, the curvature of the response surface is smallest along the first principal axis (X_0).
[55] Task-Technology Fit (TTF) occurs along the line of congruence (Y = X).
[56] The curvature along the line of congruence (Y = X) indicates changes in *use* when TTF occurs.
[57] The lack of Task-Technology Fit (TTF) occurs along the line of incongruence (Y = -X).

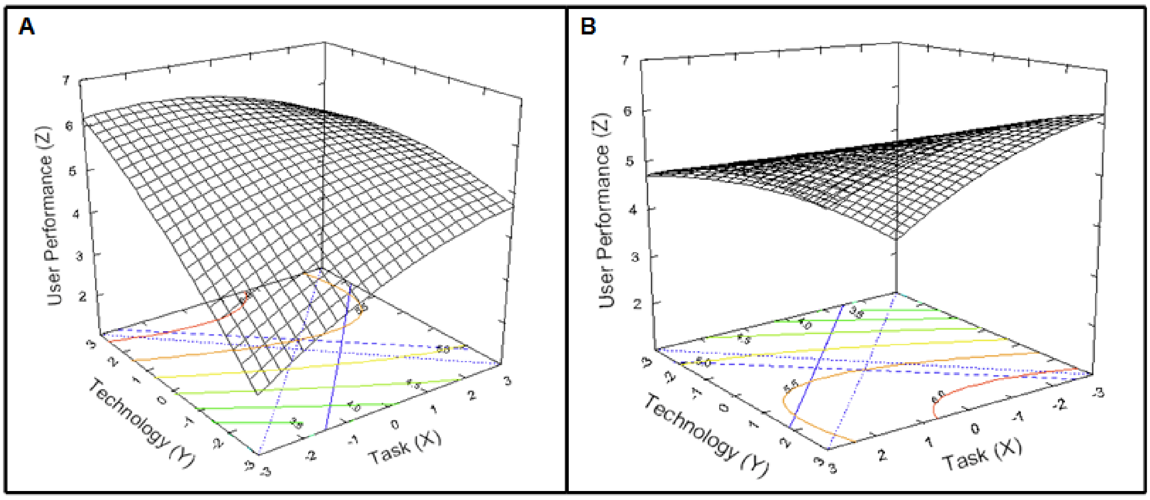

Figure 7.12. Response Surface: Task-Technology Fit (TTF) on User Performance: Front (a) and Rear (b)

The first principal axis is not significantly different [t = 0.006 (p_{11}), t = 0.000 ($-p_{10}/p_{11}+1$)] from the line of congruence (Y = X). As such, a perfect fit between the task and technology leads to maximal user performance. The upward slope along the line of congruence (Y = X) is positive but not significant (a_1 = 0.493, *t* = 1.394). The curvature along the line of congruence (Y = X) was positive but not significant (a_2 = 0.007, *t* = 0.068), indicating that the relationship between TTF and user performance is linear. Thus the curvature along line Y = X does not significantly change for CHW performance. The downward slope along the line of incongruence (Y = -X) was negative but not significant (a_3 = -0.245, *t* = -0.616). As such, a lack of fit between the CHW task and mHealth tool leads to a decrease in user performance. The curvature along the line of incongruence (Y = -X) was negative but not significant (a_4 = -0.175, *t* = -0.569), further indicating a linear relationship between TTF and user performance. The curvature along line Y = -X did not, therefore, change significantly for CHW performance. The lateral shift (Atwater, Ostroff, Yammarino and Fleenor, 1998)[58] in use and user performance, in the surface along and perpendicular to the line of congruence (Y = X) was determined as follows:

$$\frac{b_2 - b_1}{2\,(b_3 - b_4 + b_5)}$$

The lateral shift in use in the surface along the line of congruence (Y = X) was positive (7.784), indicating movement of approximately eight units toward the region where

[58] This is an indicator of whether the lowest *use* and *user performance* levels are laterally displaced from line (Y = X).

functional support levels exceed user needs (Y > X). At this point, the technology over-fits the task. As such, when mHealth tool functions over-fit user needs, there is a steep decline in CHW dependence on use. However, the lateral shift in user performance in the surface along the line of congruence (Y = X) was negative (-0.700), indicating movement of approximately one unit toward the region where user needs exceed functional support levels (Y < X). Along this surface, the technology under-fits the task such that when mHealth tool functions under-fit user needs, there is a steep decline in the effectiveness, efficiency, and quality, of patient care.

7.6 Discussion

7.6.1 Mobility Interdependence Support Fit

The interaction between the CHW task need for mobility and mHealth tool support for interdependence, has a negative effect on both use and user performance. This cross-product pairing is associated with lower CHW dependence on the mHealth tool, and minimized effectiveness, efficiency, and quality of patient care. Graphical plots of the interaction effects of this paired fit show that when there is high task mobility, mHealth tool dependence and CHW performance are not contingent on support for interdependence. On the contrary, in a technology user environment characterized by low task mobility, support functions for interdependence drive higher mHealth tool use dependence and better CHW performance. It is evident from findings that these interactions can influence a decline in CHW mHealth tool dependence and levels of CHW performance. In terms of tool dependence, Dishaw (1994) observed that it is possible that certain non-matched TTF configurations will be associated with lower usage (p. 37).

7.6.2 Mobility Information Dependency Support Fit

The interaction between the CHW task need for mobility and mHealth tool support for information dependency has a negative effect on user performance. This cross-product pairing is associated with lower patient care effectiveness, efficiency, and quality. Graphical plots of the interaction effects of this paired fit show that when there is high task mobility, CHW performance is not contingent on support for information dependency. However, when user task mobility is low, support functions for information dependency drive higher CHW performance. These findings lend credence to the possibility that TTF configurations will be associated with lower task performance, adding support to Dishaw's (1994, p. 37) observation that non-matched TTF configurations would lead to lower levels of tool usage.

7.6.3 Information Dependency Time Criticality Support Fit

The interaction between the CHW task need for information dependency and mHealth tool support for time criticality has a positive effect on user performance. This cross-product pairing is associated with higher patient care effectiveness, efficiency, and quality. This interaction, however, does not have substantive effects on use. Thus it appears that CHW dependence on the mHealth tool is not conditioned upon this interaction fit. The positive performance effects observed represent an affirmation of Dishaw's (1994) observation that user needs can be indirectly supported by tool functions. This is reflective of potential co-dependence between certain otherwise incompatible task and technology characteristics in a particular context (p 125).

7.6.4 Simultaneous Fit as Moderation

The sixteen cross-product fit interactions identified and modelled in this study for their combined effects, together with task and technology characteristics, appears to be positively and significantly associated with the higher dependence of CHWs on the mHealth tool and their enhanced effectiveness, efficiency, and quality, in the delivery of patient care. This configuration of TTF Moderation as interaction uniquely incorporates both primary, on-diagonal, and secondary, off-diagonal interactions, that are observed for their effects on use and user performance, without a preference for matching characteristics. As such, each combination is representative of a different mode of the mHealth tool's functional support for CHW task needs. Notably, this finding lends support to Goodhue, Littlefield, and Straub's (1997) observation that technology must encompass every tool function that is necessary for user task performance (p. 456).

7.6.5 Non-Linear Fit as Moderation

The analysis of non-linear impacts on use and user performance represents a perspective of task-technology equilibrium. This is a mechanism that allows for more dynamic and complex insights into the effectiveness of TTF, and is useful for observing the degree to which IT functions influence levels of tool use and user performance. Findings show that a perfect fit between the CHW task and mHealth technology has a positive effect on use. Seemingly, this fit is indicative of a higher dependence among CHWs on the mHealth tool such that without it, this dependence is diminished. This finding is consistent with Yang, Kang, Oh and Kim's (2013) observation that fit as the congruence between the task and technology leads to maximal levels of tool usage (p. 709). Similarly, the fit between CHW task and mHealth technology components is positively associated with user performance. CHWs thus perceive themselves as delivering higher quality patient care, more effectively and efficiently. This finding lends credence to a prior finding that congruent task and technology components lead to optimal user performance (Yang, Kang, Oh and Kim 2013 p. 709).

It is noteworthy that when there is excessive mHealth tool function support for CHW tasks, there appears to be a lower dependence on the technology. Yet, with insufficient functionality, tool users appear to perceive that they deliver lower quality patient care, less effectively and efficiently. These findings signify 'IT deficiency', the supply of tool functions that are insufficient for the levels users would require to perform their tasks, and 'IT surplus', the supply of tool functions that exceed user task requirements (Yang et al., 2013, p. 700). These two extremes both represent a misfit, where the former is an under-fit and the latter an over-fit (Gupta, 2003). In prior research, these misfits have been observed to have adverse effects on task productivity (Oh and Pinsonneault, 2007). The under-fit of the technology to the task results in users not optimizing tool functions for higher performance, thereby compromising their effectiveness (Gupta, 2003). Moreover, an over-fit leads to declining information accessibility and processing performance, and has been attributed to a proliferation of support functions that may be deemed by the technology user to be either excessive or redundant (Jarvenpaa, 1989).

7.6.6 Implications for Research

There are four emergent implications for research arising from the findings discussed in this chapter.

First, as was the case for TTF as Matching, a TTF matrix was used to configure sixteen possible interactions of CHW needs and mHealth tool functions. This is a useful analytical tool for identifying fit combinations and represents a versatile approach to configuring and examining multiple TTF representations for use and user performance effects.

Second, findings indicate that cross-product interactions together with task and technology predictors combine to enhance CHW dependence on the mHealth tool and task performance. This is indicative of the importance of examining TTF as the simultaneous effect of multiple task and technology interactions, in concert with task and technology characteristics as drivers of use and user performance. As such, researchers must anticipate that whereas each of the observed interactions are distinctive pairings, their collective impact may be useful for explaining use and user performance, although as suggested in this study, would nevertheless warrant further investigation.

Third, significant cross-product TTF interactions were identified as important. For instance, the interaction of information dependency and time criticality support was identified as a positive contributor to CHW perceptions of their task performance. However, another interaction between mobility and information dependency support had an inverse effect on the same. Similarly, the TTF interaction of mobility and interdependency support had a negative effect on mHealth tool dependence and CHW task performance. Both positive and negative interactions constitute value-added feedback on those TTF combinations that are functional or dysfunctional in a particular context.

Fourth, the use of an atomistic approach (Yang et al., 2013), said to involve the articulation and measurement of separate components (p. 712), represents a more realistic, nuanced perspective of TTF impacts. This novel approach can be used in subsequent research to further investigate TTF as interaction. Furthermore, the in depth analysis of differential use and user performance effects modelled using three-dimensional surfaces signifies a more enriching approach to testing TTF for non-linearity.

7.6.7 Implications for Practice

There are two emergent implications for practice arising from the findings discussed in this chapter.

First, findings indicate that cross-product interactions of user needs and mHealth tool functions enhance CHW dependence on their use for patient care effectiveness, efficiency, and quality. These co-dependent fit characteristics constitute practicable information for future mHealth designs. Results represent practical insights into the design of mHealth tools that incorporate simultaneous cross-functional support for multiple CHW tasks. Moreover, findings represent essential guidelines with which to enhance mHealth tool usability. As such, designers ought to focus more on user responsiveness and tool versatility.

Second, these findings are useful as guidelines on how increases or decreases in functional support relate to mHealth tool use and CHW performance. This sets a particularly important benchmark that mHealth tool designers can use to gauge the sensitivity of functional support to user task needs. Moreover, findings indicate that excessive or insufficient functional mHealth tool support for CHW needs may have negative use and user performance impacts. Consequently, mHealth tool designers must be cognizant of these task-technology sensitivities in order to establish equilibrium between supporting functions and CHW needs.

7.7 Chapter Conclusion

The purpose of this chapter was to adapt Venkatraman's (1989) Fit as Moderation perspective to test the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. Sixteen pairs of interacting task and technology characteristics were examined. Both primary (on-diagonal) and secondary (off-diagonal) fit interactions were examined for their effects on mHealth tool use and CHW performance.

First, one off-diagonal fit interaction was found to be significant for use. This was between the task characteristic of mobility and the technology characteristic of interdependence. Second, three off-diagonal fit interactions were found to be significant for user performance. These were between mobility and interdependence, mobility and information dependency support, and information dependency and time criticality support. It was evident that cross-product interactions between non-matching task and technology characteristics can influence, either positively or negatively, mHealth tool dependence, and the effectiveness, efficiency, and quality with which CHWs deliver patient care.

TTF was also examined for non-linear interaction effects on mHealth tool use and CHW performance.

It was found that perfect congruence (fit) between the task and technology leads to the highest levels of use. However, it was also observed that incongruence (misfit) between the task and technology leads to lower levels of use. It was observed that perfect congruence (fit) between the CHW task and the mHealth tool technology leads to the highest levels of user performance. However, it was also found that incongruence (misfit) between the CHW task and the mHealth tool technology leads to lower levels of performance. Results of further testing indicated that an over-fit of the mHealth tool to the CHW task could lead to a steep decline in use. These results also indicated that an under-fit of the mHealth tool to the CHW task could lead to a steep decline in user performance. It was evident that the relationships between TTF and mHealth tool use and CHW performance were more linear than non-linear in nature. Moreover, increases or decreases in functional support for user needs can have positive or negative effects on mHealth tool use dependence and the effectiveness, efficiency, and quality with which CHWs deliver patient care.

In Chapter 7, TTF as Moderation and its effects on use and user performance was examined. In Chapter 8, TTF as Mediation and its effects on use and user performance is examined.

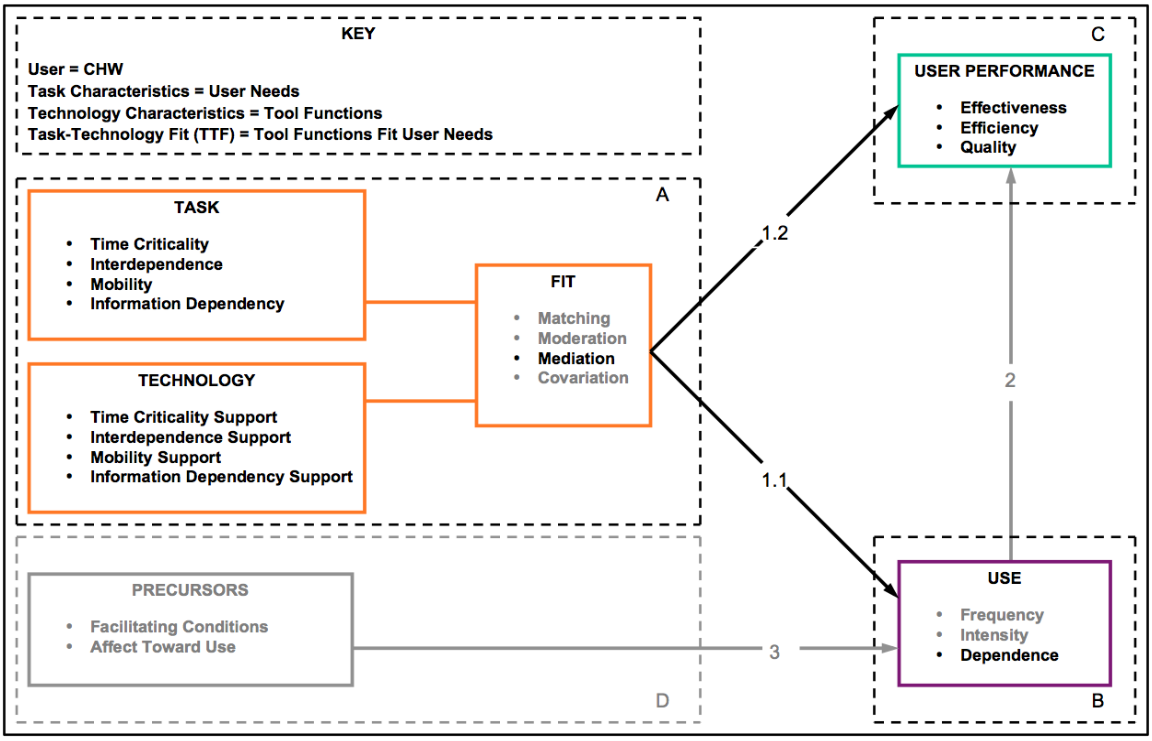

Figure 7.13. Task-Technology Fit (TTF) as Mediation

8 The Effects of Task-Technology Fit (TTF) as Mediation on Use and User Performance

This chapter is an updated version of Gatara, M. and Cohen, J.F (2014) The Mediating Effect of Task-Technology Fit on mHealth Tool Use and Community Health Worker Performance in the Kenyan Context – *Proceedings of the 8th International Development Informatics Association Conference (IDIA)*, Port Elizabeth, South Africa, pp. 323-336.

8.1 Introduction

The purpose of this chapter is to employ the Fit as Mediation perspective (Venkatraman, 1989) to examine the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. In Chapter 4 it was established that Fit as Mediation (Venkatraman, 1989) has been used to examine the effects of TTF in contexts such as the use of Decision Support Systems (DSSs) (Goodhue and Thompson, 1995), academic information systems (Staples and Seddon, 2004), and Information Communication and Technologies (ICTs) for patient care (Junglas et al., 2009). In this chapter, Fit as Mediation comprises four sets each representing a perceived intervening mechanism in the relationship between CHW task and technology characteristics and use and user performance. The concept of TTF as Mediation is discussed in Section 8.2.

8.2 Task-Technology Fit (TTF) as Mediation

In this chapter, TTF is conceptualized from the perspective of Fit as Mediation (Venkatraman, 1989). From this perspective, 'fit' is positioned as a significant intervening mechanism between antecedent and consequent variables (Venkatraman, 1989 p. 428). Within TTF, 'Fit' as perceived by the user has been positioned as a mediator between task and technology characteristics, and use and user performance (Goodhue and Thompson, 1995, p. 220). Dishaw (1994) observed that the perceived fit construct was initially examined independent of the task and technology (p. 63). However, its effects on use and user performance are observable (Staples and Seddon, 2004). Tool or system users must perceive a fit between characteristics of their task and the technology used, where such perceptions of 'fit' would influence how they use the tool, and ultimately perceive its impacts on their performance. Whereas TTF Moderation and Matching are computed, TTF Mediation is a user- perceived construct, and thus a manifestation of a cognitive fit process[59] (Vessey, 1991). Unlike computation which involves the bi-variate fit configuration between task and technology characteristics, perception represents a user-evaluated fit between the two variables. In contrast to the Moderation and Matching 'fit' perspectives, perceived TTF was examined as a mediating construct, uniquely positioned to intervene between antecedent user needs and tool functions, and consequent use and user performance outcomes. The corollary is that TTF as Mediation can be recognized as both a user-evaluated and intervening mechanism, essentially becoming a dual-purpose construct. Notably, in comparison to the Matching and Moderation fit perspectives examined in this study, TTF as Mediation was found to have less explanatory power for use and user performance.

8.3 Conceptual Model

8.3.1 The Link between Task-Technology Fit (TTF) as Mediation and Use and User Performance

'Fit' as a perceived intervening mechanism, impacts use and user performance (Dishaw, 1994). The link between TTF as Mediation and use and user performance is shown in Figure 8.1.

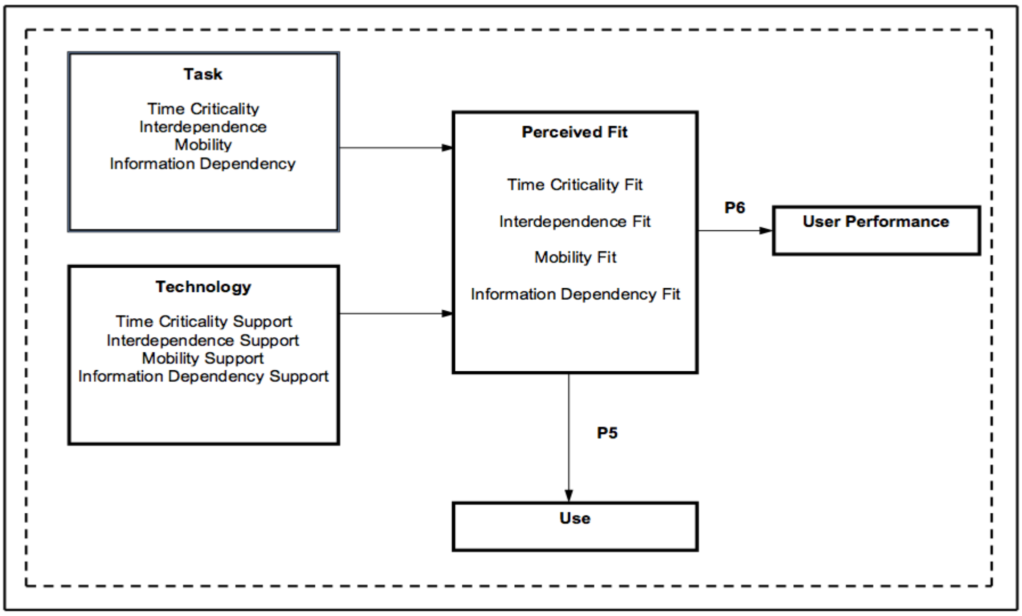

Figure 8.1. The Link between Task-Technology Fit (TTF) as Mediation and Use and User Performance

[59] The concept of Cognitive Fit was introduced and discussed in Section 4.2.1 of Chapter 4.

If the technology is perceived to fit the task performed, then use and user performance improve. This is because if users use technology because of its utility, then they are capable of evaluating whether tool or system functions fit their needs in performing their tasks (Staples and Seddon, 2004). Consequently, users will evaluate technologies based on the extent to which they perceive that tool or system functions meet their task needs. For optimal use and user performance, users must perceive the extent to which the technology used fits the task performed (Goodhue, 1995; Goodhue et al., 2000). In the mHealth context, the perceived fit between mHealth tool and CHW task characteristics is expected to improve use and user performance. As such, CHWs who perceive that the functional support available to them fits their needs will become more dependent on the mHealth tool, and use it more effectively and efficiently to deliver patient care of higher quality. Therefore mHealth tool use and CHW performance are expected consequences of a cognitive process through which the user evaluates the fit of the technology provided to the task performed.

To examine the link between TTF as Mediation and use and user performance, the following propositions are formulated:

Proposition 5 (P5): *Perceived Fit will mediate between task (need) and technology (function) characteristics and use.*
Proposition 6 (P6): *Perceived Fit will mediate between task (need) and technology (function) characteristics and user performance.*

The following sub-propositions are derived.

Proposition 5a (P5a): *Perceived time criticality fit will mediate the effects of time criticality of tasks and time criticality tool support characteristics on mHealth tool use.*
Proposition 6a (P6a): *Perceived time criticality fit will mediate the effects of time criticality of tasks and time criticality support tool characteristics on CHW performance.*
Proposition 5b (P5b): *Perceived interdependence fit will mediate the effects interdependence of tasks and interdependence support tool characteristics on mHealth tool use.*

Proposition 6b (P6b): *Perceived interdependence fit will mediate the effects interdependence of tasks and interdependence support tool characteristics on CHW performance.*

Proposition 5c (P5c): *Perceived mobility fit will mediate the effects mobility of tasks and mobility support tool characteristics on mHealth tool use.*

Proposition 6c (P6c): *Perceived mobility fit will mediate the effects mobility of tasks and mobility support tool characteristics on CHW performance.*

Proposition 5d (P5d): *Perceived information dependency fit will mediate the effects information dependency of tasks and information dependency support tool characteristics on mHealth tool use.*

Proposition 6d (P6d): *Perceived information dependency fit will mediate the effects information dependency of tasks and information dependency support tool characteristics on CHW performance.*

The methods used to examine the impact of TTF as Mediation on use and user performance, are discussed in Section 8.4.

8.4 Methods

8.4.1 Sampling, Instrument and Measures

Dataset 1 (n = 201) is used in this chapter. Dataset 1 is described in detail in Section B.1 of Appendix B. The dataset consists of responses from CHW mHealth tool users in the counties of Siaya, Nandi, and Kilifi. A structured questionnaire survey instrument was used to collect the data. The measures for CHW task characteristics, mHealth technology characteristics, perceived fit, use and user performance, were developed as described in Appendix E. These constructs were tested for multi-collinearity, reliability and validity, and final measures were used in subsequent analyses as per the procedures and criteria outlined in in Sections G.1 and G.2 of Appendix G.

8.4.2 Task-Technology Fit (TTF) as Mediation

TTF as Mediation was operationalized as the intermediate variables of *perceived time criticality fit*, *perceived interdependence fit*, *perceived mobility fit*, and *perceived information dependency fit*.

PLS-SEM mediator analysis with bootstrapping procedures[60] (Preacher and Hayes, 2004; Hair et al., 2014) were used to examine the direct effects of task and technology characteristics on use and user performance, and their indirect effects through these intermediaries. A more common approach to testing the significance of mediating effects is the Sobel (1982) test, which is used to examine the relationship between independent and dependent variables, including and excluding the mediation construct (Helm, Eggert and Garnefeld, 2010). This test, however, relies on distributional assumptions that are not consistent with the non-parametric PLS-SEM method. In addition, the parametric assumptions of the test do not hold for the indirect effect. Moreover, the test lacks statistical power, and unstandardized path coefficients are required as input for the test statistic (Hair et al., 2014, p. 223). As such, it has been recommended that researchers must instead bootstrap the sampling distribution of the indirect effect, a technique that applies to both simple and multiple mediator models (Preacher and Hayes, 2004, 2008). Unlike the Sobel test, bootstrapping makes no assumptions about the sampling distribution of the statistics and can be applied with more confidence. Furthermore, the approach has been observed to exhibit greater statistical power. Thus bootstrapping is not only more superior, but better suited to the PLS-SEM method. For these among other reasons, researchers have dismissed the Sobel test for mediation analyses, particularly in PLS-SEM studies (Klarner, Sarstedt, Hoeck and Ringle, 2013), opting for bootstrapping as the superior alternative (Henseler et al., 2009; Sattler, Volckner, Riediger and Ringle, 2010).

In this chapter, structural path models were first estimated to test the mediating effects of each of the specified intermediate variables as a perceived TTF construct. Second, a structural path model was estimated to test the combined mediating effect of all four specified perceived TTF constructs. Coefficients of determination (R^2 values) of the endogenous constructs use and user performance were used to determine the predictive accuracy[61] of the estimated PLS structural path models (Hair et al., 2014, p. 174), and

[60] The significance of direct and indirect effects were tested using 5000 sub-samples (Efron and Tibshirani, 1986; Davison and Hinkley, 1997; Preacher and Hayes, 2008).

[61] R^2 values of approximately 0.670, 0.333, and 0.190 are substantial, moderate, and weak, respectively (Chin, 1998; Urbach and Ahlemann, 2010, p. 21).

Stone-Geisser's Q^2 values (Geisser, 1974; Stone, 1974) of use and user performance were used to determine their predictive relevance[62] (Hair et al., 2014, p. 178).

Results of the structural path model estimates of TTF as Mediation are discussed in Section 8.5.

8.5 Results

The structural path models estimated to test TTF mediating effects of *perceived time criticality fit (model A)*, *perceived interdependence fit (model B)*, *perceived mobility fit (model C)*, and *perceived information dependency fit (model D)*, are depicted in Figure 8.2.

[62] Q^2 values larger than zero for a certain reflective endogenous latent variable are indicators of predictive relevance (Henseler et al., 2009, Hair et al., 2014, p. 178).

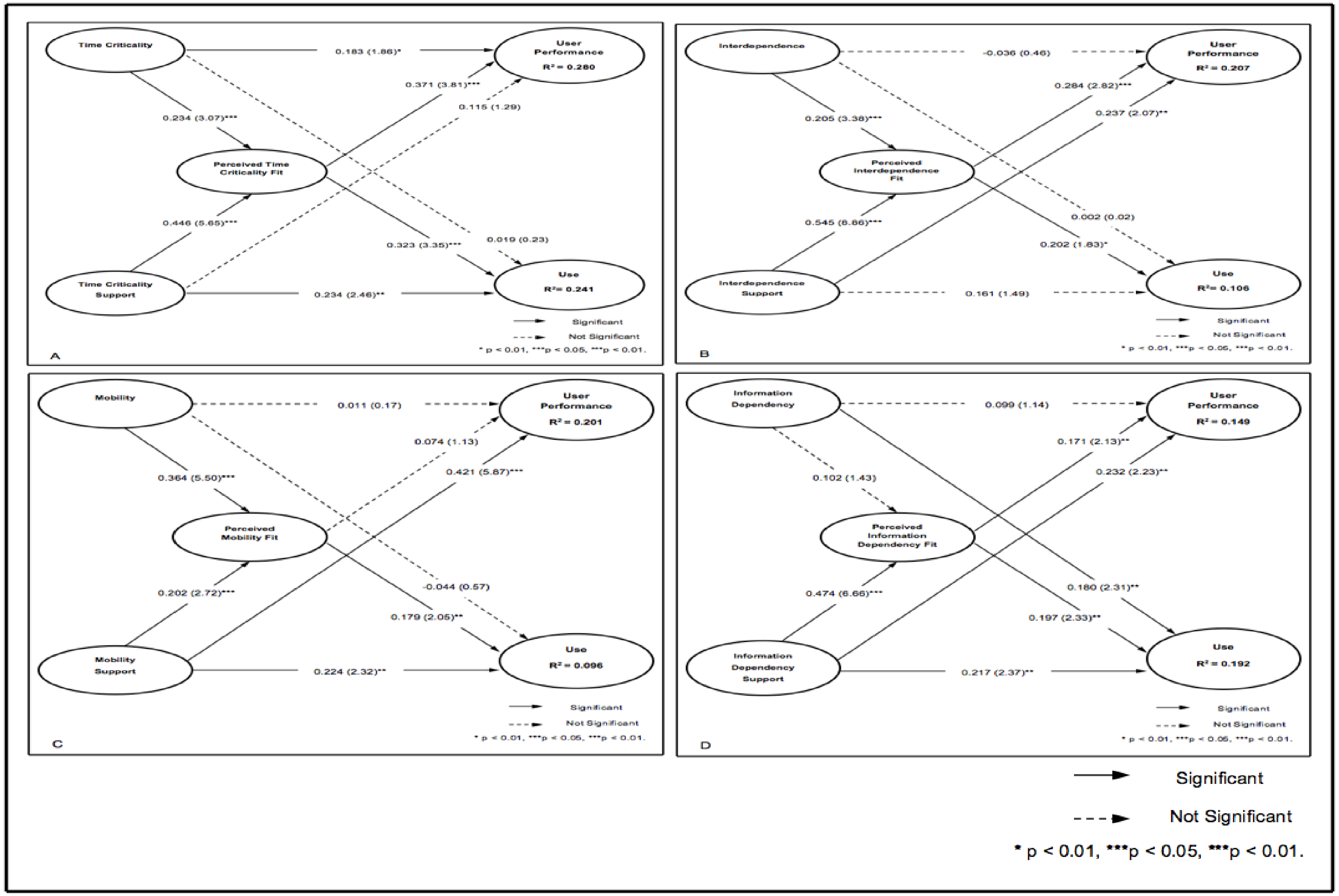

Figure 8.2. Path Models: Task-Technology Fit (TTF) as Mediation

8.5.1 Perceived Time Criticality Fit

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path model estimated to test *perceived time criticality fit* are summarized in Table 8.1.

Table 8.1. Structural Path Model Results: Perceived Time Criticality Fit					
Path	Coefficient	*t*	*p*	Significance	90% CI
Time Criticality → Perceived Time Criticality Fit	0.234 ^{p1}	3.07	0.00	***	[0.11, 0.36]
Time Criticality Support → Perceived Time Criticality Fit	0.446 ^{p1}	5.65	0.00	***	[0.32, 0.58]
Time Criticality → Use	0.019 ^{p3}	0.23	0.82	NS	[-0.11, 0.15]
Time Criticality Support → Use	0.234 ^{p3}	2.46	0.01	**	[0.08, 0.39]
Perceived Time Criticality Fit → Use	0.323 ^{p2}	3.35	0.00	***	[0.16, 0.48]
Time Criticality → User Performance	0.183 ^{p3}	1.86	0.07	*	[0.02, 0.34]
Time Criticality Support → User Performance	0.115 ^{p3}	1.29	0.20	NS	[-0.03, 0.26]
Perceived Time Criticality Fit → User Performance	0.371 ^{p2}	3.81	0.00	***	[0.21, 0.53]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 8.1 indicate that *time criticality* (*t* = 3.07, p < 0.01) and *time criticality support* (*t* = 5.65, p < 0.01) had significant positive effects on *perceived time criticality fit*. *Time criticality support* (*t* = 2.46, p < 0.01) and *perceived time criticality fit* (*t* = 3.35, p < 0.01) had significant positive effects on *use*. *Perceived time criticality fit* had a significant positive effect on *user performance* (*t* = 3.81, p < 0.01). *Time criticality* did not have a significant effect on *use* (*t* = 0.23), but had a positive significant effect on *user performance* (*t* = 1.86, p < 0.10). The significance of the indirect effects of *perceived time criticality fit* was tested. In addition, the mediating strength of *perceived time criticality fit* was determined. Indirect effect sizes, bootstrapping standard errors, *t* values, and VAF values are summarized Table 8.2.

Table 8.2. Indirect Effect and Mediation Strength Results									
Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	*t*	Significance	VAF	
								Value	**%**
Time Criticality → Use	0.019	*Time Criticality → Perceived Time Criticality Fit → Use*	0.076	0.095	0.034	2.24	**	0.800	80%
Time Criticality Support → Use	0.234	*Time Criticality Support → Perceived Time Criticality Fit → Use*	0.144	0.378	0.058	2.48	**	0.380	38%
Time Criticality → User Performance	0.183	*Time Criticality → Perceived Time Criticality Fit → User Performance*	0.087	0.270	0.042	2.07	**	0.322	32%
Time Criticality Support → User Performance	0.115	*Time Criticality Support → Perceived Time Criticality Fit → User Performance*	0.165	0.280	0.056	2.95	***	0.589	59%

NS = Not Significant. *p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

(20% < = VAF < = 80%), Full mediation (VAF > 80%)

Results in Table 8.2 indicate that the effects of *time criticality* (*t* = 2.24, p < 0.05) and *time criticality support* (*t* = 2.48, p < 0.05) on *use* through *perceived time criticality fit* were significant. In addition, the effects of *time criticality* (*t* = 2.07, p < 0.05) and *time criticality support* (*t* = 2.95, p < 0.01) on *user performance* through *perceived time criticality fit* were significant. In addition, *perceived time criticality fit* accounts for 80% (VAF = 0.800) of the effect of *time criticality* on *use*, and 32% (VAF = 0.322) of the effect of *time criticality* on *user performance*. CHWs must perceive a fit before they are willing to depend on using the technology in response to the time critical nature of tasks. *Perceived time criticality fit* accounts for 38% (VAF = 0.380) of the effect of *time criticality support* on *use* and 58% (VAF = 0.589) of the effect of *time criticality support* on *user performance*. The functional support for time criticality adds to mHealth tool dependence, and perceptions of CHWs of fit result in more effective and efficient delivery of quality patient care through the tool. Since VAF values obtained are larger than 20%, the observed effects would signify the partial mediation of *perceived time criticality fit* of the effects of *time criticality* and *time criticality support* on *use* and *user performance*. Thus ***Proposition 5a (P5a)*** and ***Proposition 6a (P6a)*** are supported.

8.5.2 Perceived Interdependence Fit

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path model estimated to test *perceived interdependence fit* are summarized in Table 8.3.

Table 8.3. Structural Path Model Results: Perceived Interdependence Fit					
Path	Coefficient	*t*	*p*	Significance	90% CI
Interdependence → Perceived Interdependence Fit	0.205 ^{p1}	3.38	0.00	***	[0.11, 0.30]
Interdependence Support → Perceived Interdependence Fit	0.545 ^{p1}	8.86	0.00	***	[0.44, 0.65]
Interdependence → Use	0.002 ^{p3}	0.02	0.98	NS	[-0.13, 0.13]
Interdependence Support → Use	0.161 ^{p3}	1.49	0.14	NS	[-0.02, 0.34]
Perceived Interdependence Fit → Use	0.202 ^{p2}	1.83	0.07	*	[0.02, 0.38]
Interdependence → User Performance	-0.036 ^{p3}	0.46	0.65	NS	[-0.17, 0.09]
Interdependence Support → User Performance	0.237 ^{p3}	2.07	0.04	**	[0.05, 0.42]
Perceived Interdependence Fit → User Performance	0.284 ^{p2}	2.82	0.01	***	[0.12, 0.45]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 8.3 indicate that *interdependence* (*t* = 3.38, p < 0.01) and *interdependence support* (*t* = 8.86, p < 0.01) had significant positive effects on *perceived interdependence fit*. *Perceived interdependence fit* had significant positive effects on *use* (*t* = 1.83, p < 0.10) and *user performance* (*t* = 2.82, p < 0.01). *Interdependence support* (*t* = 2.07. p < 0.05) had a significant positive effect on *user performance*. *Interdependence* (*t* = 0.02) and *interdependence support* (*t* = 1.49) did not have a significant effect on *use*. *Interdependence* (*t* = 0.46) did not have a significant effect on *user performance*. The significance of the indirect effects was tested. The significance of the indirect effects of *perceived interdependence fit* was tested. In addition, the mediating strength of *perceived interdependence fit* was determined. Indirect effect sizes, bootstrapping standard errors, *t* values, and VAF values are summarized Table 8.4.

Table 8.4. Indirect Effect and Mediation Strength Results									
Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	*t*	Significance	VAF	
								Value	**%**
Interdependence Support → Use	0.161	*Interdependence Support → Perceived Interdependence Fit → Use*	0.110	0.271	0.028	1.77	*	0.406	41%
Interdependence → User Performance	-0.036	*Interdependence → Perceived Interdependence Fit → User Performance*	0.058	0.022	0.062	2.15	**	2.636	263%
Interdependence Support → User Performance	0.237	*Interdependence Support → Perceived Interdependence Fit → User Performance*	0.155	0.392	0.027	2.67	***	0.395	40%

*p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

Results in Table 8.4 indicate that the effect of *interdependence support* (t = 1.77, p < 0.10) on *use* through *perceived interdependence fit* was significant. In addition, the effects of *interdependence* (t = 2.15, p < 0.05) and *interdependence support* (t = 2.67, p < 0.01) on *user performance* through *perceived interdependence fit* were significant. However, the effect of *interdependence* (t = 1.46) on *use* through *perceived interdependence fit* was not significant. The mediating strength of *perceived interdependence fit* was determined. Results are summarized in Table 8.6. In addition, *perceived interdependence fit* accounts for 41% (VAF = 0.406) of the effect of *interdependence support* on *use*, and 40% (VAF = 0.395) of the effect of *interdependence support* on *user performance*. CHWs must perceive a fit before they are willing to depend on using the technology in response to the interdependent nature of tasks. The functional support for interdependence adds to mHealth tool dependence, and perceptions of CHWs of fit result in more effective and efficient delivery of quality patient care. Notably, *perceived interdependence fit* accounts for 263% (VAF = 2.636) of the negative effect of *interdependence* on *user performance* (-0.036). CHWs deliver lower quality patient care less effectively and efficiently, in response to the interdependent nature of tasks. The perceptions of CHWs of fit result in the suppression of any adverse effects of interdependent tasks on the performance of the user. Since VAF values obtained are larger than 20%, the observed effects signify the partial mediation of *perceived* *interdependence fit* of the effect of *interdependence* and *interdependence support* on *use*, and the full mediation of *perceived interdependence fit* of the effect of *interdependence* on *user performance*. Thus ***Proposition 5b (P5b)*** and ***Proposition 6b (P6b)*** are supported.

8.5.3 Perceived Mobility Fit

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path model estimated to test *perceived mobility fit* are summarized in Table 8.5.

Table 8.5. Structural Path Model Results: Perceived Mobility Fit

Path	Coefficient	*t*	*p*	Significance	90% CI
Mobility → Perceived Mobility Fit	0.364 ^{p1}	5.50	0.07	***	[0.26, 0.47]
Mobility Support → Perceived Mobility Fit	0.202 ^{p1}	2.72	0.07	***	[0.08, 0.32]
Mobility → Use	-0.044 ^{p3}	0.57	0.08	NS	[-0.17, 0.48]
Mobility Support → Use	0.224 ^{p3}	2.32	0.10	**	[0.06, 0.39]
Perceived Mobility Fit → Use	0.179 ^{p2}	2.05	0.09	**	[0.04, 0.32]
Mobility → User Performance	0.011 ^{p3}	0.17	0.06	NS	[-0.09, 0.11]
Mobility Support → User Performance	0.421 ^{p3}	5.87	0.07	***	[0.30, 0.54]
Perceived Mobility Fit → User Performance	0.074 ^{p2}	1.13	0.07	NS	[-0.03, 0.18]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 8.5 indicate that *mobility (t* = 5.50, p < 0.01) and *mobility support* (*t* = 2.72, p < 0.05) had significant positive effects on *perceived mobility fit*. *Mobility support* had a significant positive effect on *use* (*t* = 2.32, p < 0.05) and *user performance* (*t* = 5.87, p < 0.01). *Perceived mobility fit* had a significant positive effect on *use* (*t* = 2.05, p < 0.05). *Mobility* did not have a significant effect on *use* (*t* = 0.57) and *user performance* (*t* = 1.13). *Perceived mobility fit* did not have a significant positive effect on *user performance* (*t* = 0.17). The significance of the indirect effects of *perceived mobility fit* was tested. In addition, the mediating strength of *perceived mobility fit* was determined. Indirect effect sizes, bootstrapping standard errors, *t* values, and VAF values are summarized Table 8.6.

Table 8.6. Indirect Effect and Mediation Strength Results									
Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	*t*	Significance	VAF	
								Value	**%**
Mobility → Use	-0.044	*Mobility → Perceived Mobility Fit → Use*	0.065	0.021	0.036	1.81	*	3.095	309%

*p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

Results in Table 8.6 indicate that the effect of task *mobility* (t = 1.81, p < 0.10) on *use* through *perceived mobility fit* was significant. However, the effect of *mobility support* (t = 1.57) on *use* through *perceived mobility fit* was not significant. As such, its effect is not mediated but direct. The effects of *mobility* (t = 1.04) and *mobility support* (t = 1.07) on *user performance* through *perceived mobility fit* were also not significant. In addition, *perceived mobility fit* accounts for 309% (VAF = 3.095) of the negative effect of *mobility* on *use* (-0.044). CHWs depend on mHealth tools in response to the mobile nature of tasks. The perceptions of CHWs of fit result in the suppression of any adverse effects of mobile tasks on the use of the technology. Since the VAF value obtained is larger than 80%, the observed effect signifies the full mediation of *perceived mobility fit*, of the effect of *mobility* on *use*. Thus ***Proposition 5c (P5c)*** is supported. ***Proposition 6c (P6c)*** is however not supported. Evidently, users attribute performance to the mobility support provided by the tool whether or not they perceive a fit.

8.5.4 Perceived Information Dependency Fit

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals of the structural path model estimated to test *perceived information dependency fit* are summarized in Table 8.7.

Table 8.7. Structural Path Model Results: Perceived Information Dependency Fit					
Path	Coefficient	*t*	*p*	Significance	90% CI
Information Dependency → Information Dependency Fit	0.102^{p1}	1.43	0.15	NS	[-0.01, 0.22]
Information Dependency Support → Perceived Information Dependency Fit	0.474^{p1}	6.66	0.00	***	[0.36, 0.59]
Information Dependency → Use	0.180^{p3}	2.31	0.02	**	[0.05, 0.31]
Information Dependency Support → Use	0.217^{p3}	2.37	0.02	**	[0.07, 0.37]

Perceived Information Dependency Fit → Use	0.197 p2	2.33	0.02	**	[0.06, 0.33]
Information Dependency → User Performance	0.099 p3	1.14	0.26	NS	[-0.04, 0.24]
Information Dependency Support → User Performance	0.232 p3	2.23	0.03	**	[0.06, 0.40]
Perceived Information Dependency Fit → User Performance	0.171 p2	2.13	0.03	**	[0.04, 0.30]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 8.7 indicate that *perceived information dependency fit* had significant positive effects on *use* (t = 2.33, p < 0.05) and *user performance* (t = 2.13, p < 0.05). *Information dependency* (t = 2.31, p < 0.05) and *information dependency support* (t = 2.37, p < 0.05) had significant positive effects on *use*. *Information dependency support* (t = 2.23, p < 0.05) had significant user effects on *user performance*. *Information dependency* (t = 1.14) did not have significant effects on *user performance*. The significance of the indirect effects was tested. The significance of the indirect effects of *information dependency fit* was tested. In addition, the mediating strength of *perceived information dependency fit* was determined. Indirect effect sizes, bootstrapping standard errors, t values, and VAF values, are summarized Table 8.8.

Table 8.8. Indirect Effect and Mediation Strength Results

Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	t	Significance	VAF	
								Value	**%**
Information Dependency Support → Use	0.217	*Information Dependency Support → Perceived Information Dependency Fit → Use*	0.093	0.310	0.019	1.05	NS	0.300	30%
Information Dependency Support → User Performance	0.232	*Information Dependency Support → Perceived Information Dependency Fit → User Performance*	0.081	0.313	0.044	2.11	**	0.258	26%

NS = Not Significant. *p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

Results in Table 8.8 indicate that the effect of *information dependency support* on *use* (t = 2.11, $p < 0.05$) and *user performance* (t = 2.03, $p < 0.05$) through *perceived information dependency fit* was significant. However, the effects of *information dependency* on *use* (t = 1.05) and *user performance* (t = 1.00) through *perceived information dependency fit* were not. The mediating strength of *perceived information dependency fit* was determined. Results are summarized in Table 8.12. In addition, *perceived information dependency fit* accounts for 30% (VAF = 0.300) of the effect of *information dependency support* on *use* and 26% (VAF = 0.258) of the effect of *information dependency support* on *user performance*. The functional support for information dependency adds to mHealth tool dependence. Moreover, perceptions of CHWs of fit result in higher mHealth tool dependence and more effective and efficient delivery of quality patient care. Since VAF values obtained are larger than 20%, the observed effects would signify the partial mediation of *perceived information dependency fit* of the effects of *information dependency support* on *use* and *user performance*. Thus ***Proposition 5d (P5d)*** and ***Proposition 6d (P6d)*** are supported.

8.5.5 Combined Perceived Fit as Mediation

A multiple mediator simultaneous effects structural path model was estimated[63] to test the combined effects of perceived time criticality fit, perceived interdependence fit, perceived mobility fit, and perceived information dependency fit, as intermediaries in a single model. The model has significant predictive accuracy for the endogenous constructs of *use* (R^2 = 0. 289) and *user performance* (R^2 = 0. 374), and significant predictive relevance for the endogenous constructs of *use* (Q^2 = 0. 147) and *user performance* (Q^2 = 0. 222). The path coefficients, t values, p values, significance levels, and confidence intervals, of the structural path model estimated to test the combined effects of *perceived fit* are summarized in Table 8.9.

[63] A detailed description of the mediation process, including details of the formulae applied to determine these multiple mediator effects (for each of the four sets of results obtained for Table 8.9), is provided in Appendix N.

Table 8.9. Path Model Results: Perceived Fit Combined Effects		
	Path	Coefficient
1	*Task → Perceived Fit*	1.028 p1
	Perceived Fit → Use	0.461 p2
	Task → Use	0.000 p3
***Indirect Effect 1 (1)* = p^1 (1.028) x p^2 (0.461) = 0.474**		
2	*Technology → Perceived Fit*	2.313 p1
	Perceived Fit → Use	0.461 p2
	Technology → Use	0.261 p3
***Indirect Effect 2 (2)* = p^1 (2.313) x p^2 (0.461) = 1.067**		
3	*Task → Perceived Fit*	1.028 p1
	Perceived Fit → User Performance	0.383 p2
	Task → User Performance	0.051 p3
***Indirect Effect 3 (3)* = p^1 (1.028) x p^2 (0.383) = 0.394**		
4	*Technology → Perceived Fit*	2.313 p1
	Perceived Fit → User Performance	0.383 p2
	Technology → User Performance	0.401 p3
***Indirect Effect 4 (4)* = p^1 (2.313) x p^2 (0.383) = 0.886**		

As indicated in Table 8.9 four sets of results were obtained by applying formulae as detailed in Appendix N. The significance of the indirect effects in this model was determined. The significance of the indirect effects of *perceived fit* was tested. In addition, the mediating strength of *perceived fit* was determined. Indirect effect sizes, bootstrapping standard errors, *t* values, and VAF values, are summarized Table 8.10.

Table 8.10. Indirect Effect and Mediation Strength Results									
Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	*t*	Significance	VAF	
								Value	**%**
Task → Use	0.000	*Task → Perceived Fit → Use*	0.474	0.474	0.052	9.11	***	1.000	100%
Technology → Use	0.261	*Technology → Perceived Fit → Use*	1.067	1.328	0.113	9.44	***	0.803	80%
Task → User Performance	0.051	*Task → Perceived Fit → User Performance*	0.394	0.445	0.049	8.04	***	0.885	89%
Technology → User Performance	0.401	*Technology → Perceived Fit → User Performance*	0.886	1.287	0.098	9.04	***	0.688	69%

NS = Not Significant. *p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

Results in Table 8.10 indicate that *perceived fit* accounts for 100% (VAF = 1.000) of the effect of the *task* and 80% (VAF = 0.803) of the effect of the *technology* on *use*. In addition, *perceived fit* accounts for 89% (VAF = 0.885) of the effect of the *task* on *user performance* and 69% (VAF = 0.688) of the effect of the *technology* on *user performance*. It is evident that CHWs must perceive a fit before they are willing to depend on using the technology in response to the nature of the task. The functional support for the task adds to mHealth tool dependence, and perceptions of CHWs of fit result in more effective and efficient delivery of quality patient care. VAF values obtained are larger than 20% such that observed effects would signify the partial mediation of *perceived fit*, of the effects of the *technology* on *use* and *user performance*. In addition, VAF values obtained are larger than 80% such that observed effects would signify the full mediation of *perceived fit* of the effects of the *task* on *use* and *user performance*. Thus ***Proposition 5 (P5)*** and ***Proposition 6 (P6)*** are supported.

8.6 Discussion

8.6.1 Perceived Time Criticality Fit

The user perception of a fit between the mHealth tool's time criticality support and the CHW task needs to respond urgently has significant impacts on use and user performance. This perception partially mediates the effects of task and tool characteristics on use and user performance. This finding indicates that tool use and task performance may be dependent in part, on how the CHW perceives a time critical fit. This is consistent with the notion of time criticality fit of mHealth technology, such that technology meets the need for urgent patient care intervention, as having, significant, positive performance impacts on health service delivery (Junglas, Abraham, and Ives 2009, p. 641).

8.6.2 Perceived Interdependence Fit

The user perception of a fit between the mHealth tool's interdependence support and the need for CHWs to co-operate as co-workers is significant for use and user performance. This perception partially mediates the effects of tool characteristics on use and user performance, and fully mediates the effects of task characteristics on user performance. Where full mediation was evident, there was inconsistent mediation (MacKinnon, Fairchild and Fritz, 2007) such that a suppressor effect was observed (p. 174). As such, a perceived fit between the CHW task and the mHealth tool absorbs or suppresses any negative effects that interdependence needs may have on user performance. Therefore in the absence of a perceived fit, interdependence characteristics do not influence CHW dependence on mHealth tool use or patient care.

8.6.3 Perceived Mobility Fit

The user perception of a fit between the mHealth tool's mobility support and the need for CHWs to move from one location to another is significant for use. This is a full mediator of mobility need effects on mHealth tool dependence, thereby signifying a suppressor effect, a case of inconsistent mediation (MacKinnon et al., 2007). Thus, a perceived fit between the CHW task and the mHealth tool neutralizes any negative effects that mobility needs may have on use. Evidently, mobility user need characteristics are not significant on their own. However, there was no observed mediation effect of mobility need and support effects on user performance. This means that the mobility user need and support function characteristics are sufficient drivers of the mHealth tool's contribution to effectiveness, efficiency, and quality in patient care delivery.

8.6.4 Perceived Information Dependency Fit

The user perception of a fit between the mHealth tool's information dependency support and the need for CHWs to access information is significant for use and user performance. This perception partially mediates information dependency support effects on use and user performance. This finding indicates that tool use and task performance may be dependent in part, on how the CHW perceives an information dependency fit. However, there was no observed mediation effect of information dependence need effects on use and user performance. Thus the need for information dependency alone sufficiently compels use and user performance. Evidently, a recognized need or tool function on its own can be a catalyst for user behaviour. Therefore, an implicit need is created in the mind of the technology user, compelling their tool use and task performance such that conceiving of a fit is not necessarily the only mechanism through which need influences use. However, perceived fit is still important.

8.6.5 Simultaneous Fit as Mediation

The fit dimensions of perceived time criticality, interdependence, mobility, and information dependency fit, together, have significant effects on user performance. This finding indicates that CHWs who perceive a simultaneous fit of mHealth tool support functions to their task performance needs become more dependent on use of the technology and deliver more improved patient care. This is evidence that in particular user environments, users can simultaneously acknowledge co-existent task and technology characteristics, implicitly or explicitly.

8.6.6 Implications For Research

There are four emergent implications for research arising from the findings discussed in this chapter.

First, unlike the prior two perspectives of Matching and Moderation where ‘fit’ is calculated, TTF was conceptualized in this chapter as a perceptual construct. This user perception of ‘fit’ comprised multiple dimensions each examined as intervening mechanisms positioned between user needs and tool functions, and technology use and task performance. In prior TTF research, the construct of perceived fit has not been explicitly tested as a mediating variable. The empirical testing of a specified fit construct as both perceptual and mediating thus represents a more refined and substantive approach to TTF conceptualization and contribution over prior works.

Second, it was found that certain perceived fit dimensions mediated either partially or fully, tool function effects on use and user performance. For instance, perceived time criticality had partial mediating effects, significantly intervening between time criticality needs and functions, and use and user performance. However, perceived mobility fit was a full mediator of mobility need effects on mHealth tool use, but was insignificant for CHW performance. These findings indicate that in some instances, the perception of either a task need or functional support are sufficient causes for CHW dependence on the mHealth tool, and patient care effectiveness, efficiency, and quality. However, perceiving a fit of the technology to the task amplifies these user perceptions and as such, influences use and user performance.

Third, suppressor effects were observed. For example, perceived interdependence fit suppresses the negative effects of interdependence needs on CHW performance. In some cases, therefore, CHW dependence on the mHealth tool and effective and efficient, quality patient care delivery, is wholly dependent on users perceiving that functional support fits their task needs. This observation is important for researchers in seeking to better understand TTF as a mediating mechanism.

Fourth, users with multiple needs can perceive, recognize, and reflect on the multiple dimensions of fit. Therefore, the presence of multiple, perceived fits between the CHW task and mHealth technology is recognized as a possibility beyond singular TTF dimensions that are observed initially. This implies that it is possible to observe CHW needs and mHealth tool functions as co-existent characteristics in a shared user environment and accordingly, anticipate simultaneous use and user performance impacts in TTF research.

8.6.7 Implications For Practice

There are two emergent implications for practice arising from the findings discussed in this chapter.

First, CHWs depend more on the mHealth tool and deliver quality patient care more effectively and efficiently when they perceive that functional support fits their needs. The findings observed could therefore constitute guidelines with which mHealth tool designers can diagnose and then prioritize CHW preferences to design responsive, user-centric support interfaces.

Second, CHWs perceiving that they have a need for interdependence and mobility adversely affects their levels of mHealth tool dependence and delivery of patient care. These findings could inform the development of enhanced mHealth tool functionality to aid designers in counteracting any negative user perceptions of task requirements that may arise. In the tool development phase particularly, fit perception scores must be obtained from technology users as feedback. Where these indices are found to be low, mHealth tool designers ought to reflect on support functions to determine how best to enhance fit and thereby improve user experience engaging with the technology, and by extension, improve user ratings.

8.7 Chapter Conclusion

The purpose of this chapter was to adapt Venkatraman's (1989) Fit as Mediation perspective to test the effects of a perceived Task-Technology Fit (TTF) on mHealth tool use and CHW performance. Perceived time criticality fit, perceived mobility fit, perceived interdependence fit and perceived information dependency fit, were all significant for mHealth tool use and CHW performance. Only perceived mobility fit was not significant for CHW performance. Perceived fit fully mediated the effects of the CHW task's mobility on mHealth tool use, but only partially mediated the effects of the CHW task's time criticality on mHealth tool use. Perceived fit partially mediated the effects of the mHealth technology's time criticality support, interdependence support, and information dependency support, on mHealth tool use. Perceived fit partially mediated the effects of the CHW task's time criticality on CHW performance, but did not mediate the effects of interdependence, mobility, and information dependency, on CHW performance. Perceived fit fully mediated the effects of the mHealth technology's time criticality support on CHW performance, but only partially mediated the effects of information dependency and interdependence support, on CHW performance. Mobility support retained a direct effect on CHW performance. Combined, perceived time criticality fit, perceived mobility fit, perceived interdependence fit, and perceived information dependency fit, fully mediated the effects of the CHW task's characteristics on use and user performance, but only partially mediated the effects of the mHealth technology's characteristics on use and user performance. Taken together, perceived time criticality fit, perceived mobility fit, perceived interdependence fit, and perceived information dependency fit, can be perceived by the user either independently or as a combination. In either case, a perceived fit could mediate between task and technology characteristics, and mHealth tool use and CHW performance.

Results of tests of TTF as Mediation and its effects on use and user performance are summarized in Table 8.11.

Table 8.11. Findings		
Proposition		Result
P5a	Perceived time criticality fit will mediate the effects of time criticality of tasks and time criticality tool support characteristics on mHealth tool use.	Supported
P6a	Perceived time criticality fit will mediate the effects of time criticality of tasks and time criticality support tool characteristics on CHW performance.	Supported
P5b	Perceived interdependence fit will mediate the effects interdependence of tasks and interdependence support tool characteristics on mHealth tool use.	Supported
P6b	Perceived interdependence fit will mediate the effects interdependence of tasks and interdependence support tool characteristics on CHW performance.	Supported
P5c	Perceived mobility fit will mediate the effects mobility of tasks and mobility support tool characteristics on mHealth tool use.	Supported
P6c	Perceived mobility fit will mediate the effects mobility of tasks and mobility support tool characteristics on CHW performance.	Not Supported
P5d	Perceived information dependency fit will mediate the effects information dependency of tasks and information dependency support tool characteristics on mHealth tool use.	Not Supported
P6d	Perceived information dependency fit will mediate the effects information dependency of tasks and information dependency support tool characteristics on CHW performance.	Supported
P5	Perceived Fit will mediate between task (need) and technology (function) characteristics and use.	Supported full mediation
P6	Perceived Fit will mediate between task (need) and technology (function) characteristics and user performance.	Supported partial mediation

In Chapter 8, TTF as Mediation and its effects on use and user performance was examined. In Chapter 9, TTF as Covariation and its effects on use and user performance is examined.

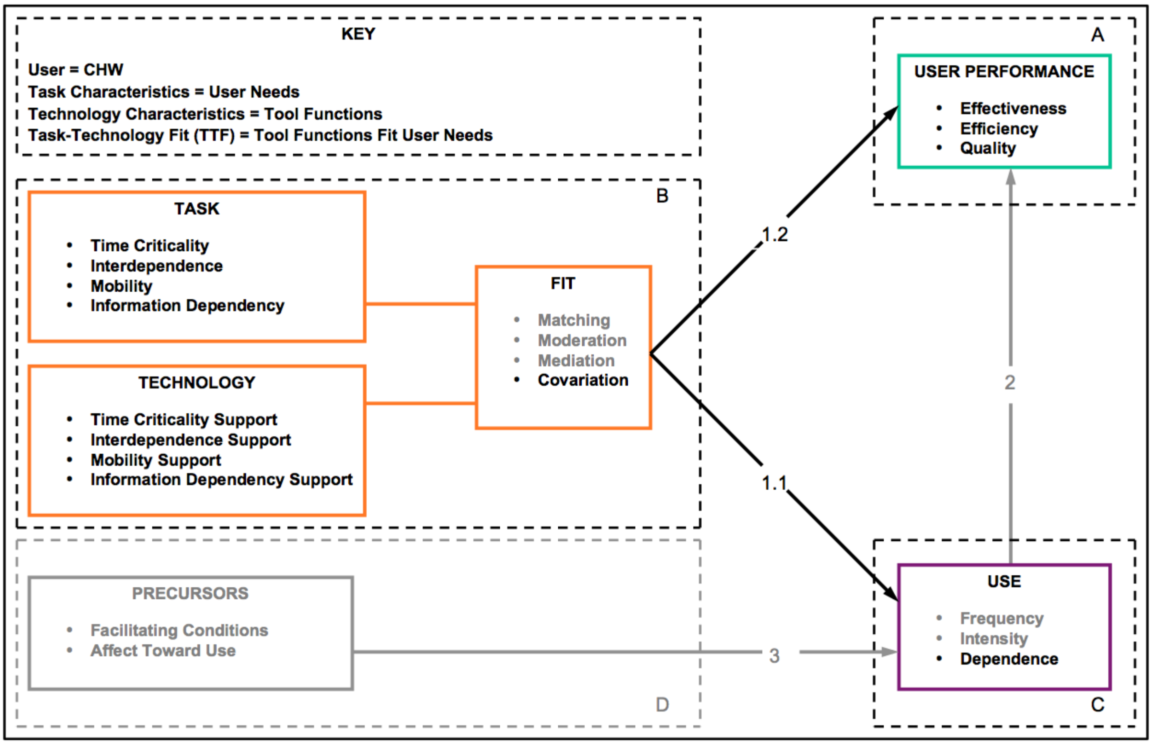

Figure 8.3. Task-Technology Fit (TTF) as Covariation

9 The Effects of Task-Technology Fit (TTF) as Covariation on Use and User Performance

This chapter is an updated version of Gatara, M. and Cohen, J.F. (2014) Mobile-Health Tool Use and Community Health Worker Performance in the Kenyan Context: A Task-Technology Fit Perspective – *Proceedings of the Southern African Institute for Computer Scientists and Information Technologists (SAICSIT) Annual Conference* 2014, Pretoria, South Africa, pp. 1-10.

9.1 Introduction

In Chapter 8, the Fit as Mediation perspective (Venkatraman, 1989) was adopted and used to conceptualize TTF as a perceptual intervening mechanism (p. 428) between antecedent task and technology characteristics, and consequent use and user performance outcomes. The purpose of this chapter is to employ the Fit as Covariation perspective (Venkatraman, 1989) to examine the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. In this chapter, Fit as Covariation represents the co-alignment of four interrelated CHW task and mHealth technology characteristics, subsequently examined for internally consistent effects on use and user performance outcomes. The concept of TTF as Covariation is discussed in section 9.2.

9.2 Task-Technology Fit (TTF) as Covariation

The Fit as Covariation perspective (Venkatraman, 1989) informs the conceptualization of TTF as a pattern of internal consistency among a set of underlying, interrelated, task and technology characteristics (p. 435). In this chapter, 'fit' is described as a holistic pattern or stream of concurrent user needs and tool functions. For this holistic 'fit' to manifest, the task and technology characteristics identified must be in co-alignment in order to constitute the pattern or stream through with their covariation effects can be observed (p. 436). These characteristics are the co-aligned factors that form a TTF construct that can be examined for its effects on the criteria variables of use and user performance. In essence, there must exist a central thread and internal logic that underlies a pattern which if modelled, reflects the degree of covariation among a set of attributes considered as constituent dimensions that together are dimensions of a coherent 'fit' (Venkatraman, 1989, p. 436; Segars, Grover and Teng, 1998). As such, TTF can be described as the internal consistency of a set of co-aligned user needs and tool functions that is observed for its effects on outcomes of use and user performance. Although originally specified without reference to a criterion variable, Venkatraman (1989) observed that ‘fit’ as covariation can be examined for its effects on an outcome variable such as performance. The operationalization of this ‘holistic fit’ involves its examination as a second-order factor expressed in terms of a set of first-order factors (Venkatraman, 1989). In other words, the ‘fit’ construct must be specified as a higher-order factor such that its lower-order factors represent the underlying inter-related dimensions that are in co-alignment (p. 436). In this study, these underlying co-aligned dimensions can be described as a set of first-order task and technology characteristics. This is evocative of a ‘systems approach to fit’, synonymous with the evaluation of internally consistent, inter-related underlying components, examined as a collective (Segars, 1994). In this study, the systems approach was adapted for the examination of ‘TTF’ from the ‘fit’ perspective of Covariation[64]. Notably, the Covariation ‘fit’ perspective is neither computed nor user-perceived, but is instead represented as an observable pattern termed as ‘holistic configuration’. In contrast to other perspectives of ‘fit’ examined in the present study, the paradigm of covariation ‘fit’ was observed as a state of co-alignment and internal consistency, subsequently tested for its effects on use and user performance. For covariation ‘fit’ to fully manifest however, two conditions must be satisfied. First, user needs and tool functions must be inter-related factors for their TTF co-alignment to be testable. Second, these factors must be coherent, for an internally consistent TTF between them to be observed. Thus the co-existence of task and technology characteristics in the same contextual domain, observed together for their effects, is essential. For the effects of covariation to be aptly demonstrated, these co-aligned and internally consistent task and technology characteristics must be modelled for the effects of their ‘fit’ on a set of criteria variables such as use and user performance. To this effect, the Covariation ‘fit’ perspective, is unique in that in a manner unlike Moderation, Matching, and Mediation, is considered ‘hidden’ and thus only indirectly observable.

The link between TTF as Covariation and use and user performance is discussed in Section 9.3.

[64] Two other systems ‘fit’ approaches, namely Gestalts and Profile Deviation, have been examined in prior works as alternatives to Covariation.

9.3 Conceptual Model

9.3.1 The Link between Task-Technology Fit (TTF) as Covariation and Use and User Performance

In this chapter, TTF as a second-order factor represents the co-alignment of CHW task and mHealth technology characteristics, represented as a set of first-order factors[65]. In this representation, the first-order factors are differentiated from their 'fit' as a second-order factor, as depicted in Figure 9.1.

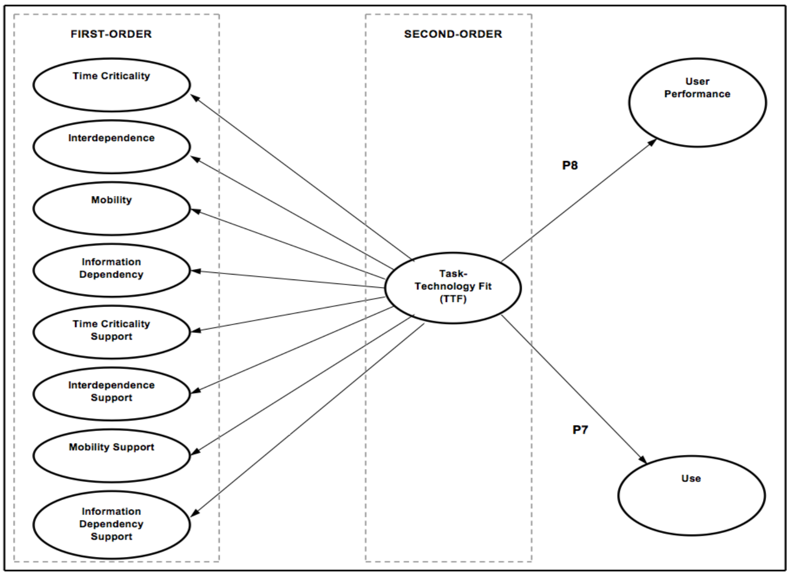

Figure 9.1. The Link between Task-Technology Fit (TTF) as Covariation and Use and User Performance

If the technology used supports the task performed then tool use and user performance levels are expected to improve (Goodhue, 1992). This is because of a pattern of alignment between user needs and tool functions. For optimal use and user performance, these co-aligned user needs and tool functions must be internally consistent. Therefore, the internally consistent, co-alignment of CHW task and mHealth tool technology characteristics would lead to enhanced use and user performance. Thus, CHWs would become more dependent on mHealth tool use and deliver higher quality patient care more effectively and efficiently.

[65] For schematic clarity, the reflective indicators of the first-order factors (task and technology characteristics) are not drawn in the models depicted in this chapter. For a detailed description of the reflective manifest indicators used to represent the dimensions of the task and technology characteristics, please refer Appendices E and G.

To examine the link between TTF as Covariation and use and user performance, the following propositions are formulated:

Proposition 7 (P7): *Fit as the internally consistent co-alignment of task (need) and technology (function) characteristics will influence use.*

Proposition 8 (P8): *Fit as the internally consistent co-alignment of task (need) and technology (function) characteristics will influence user performance.*

The methods used to examine the impact of TTF as Covariation on use and user performance are discussed in Section 9.4.

9.4 Methods

9.4.1 Sampling, Instrument and Measures

Dataset 1 (n = 201) is used in this chapter. Dataset 1 is described in detail in Section B.1 of Appendix B. The dataset consists of responses from CHW mHealth tool users in the counties of Siaya, Nandi, and Kilifi. A structured questionnaire survey instrument was used to collect the data. The measures for CHW task characteristics, mHealth technology characteristics, use and user performance, were developed as described in Appendix E. These constructs were tested for multi-collinearity, reliability and validity, and final measures were used in subsequent analyses as per the procedures and criteria outlined in in Sections G.1 and G.2 of Appendix G.

9.4.2 Task-Technology Fit (TTF) as Covariation

TTF as Covariation was operationalized as a second-order factor intermediate co-alignment construct (Venkatraman, 1989, p. 437) to form a pattern of internally consistent, conceptually-related, co-aligned, first-order task and technology characteristics, together comprising eight factors. These are a set of four time criticality, interdependence, mobility, and information dependency CHW task needs and mHealth tool support functions apiece. The second-order 'fit' of these first-order task and technology characteristics was tested for its effects on use and user performance. PLS-SEM (Hair et al., 2014) with second-order factor analyses (Venkatraman, 1989, p.436) was used to test the effect of TTF as internally consistent co-alignment on use and user performance. The purpose of second-order factor analysis is to examine covariation among a set of lower-order factors and explain it in terms of a higher-order factor representing their 'fit'. As such, 'fit' as covariation must be specified as a second-order factor with first-order factors representing its underlying, co-aligned dimensions (Venkatraman, 1989, p. 436). The use of PLS-SEM is, therefore, ideal for second-order factor analysis. The TTF construct in this chapter was modelled as a reflective first-order reflective second-order construct, using reflective-reflective Type I models (Becker, Klein and Wetzels, 2012, p. 363). In these model setups[66], the second-order construct typically comprises a set of underlying first-order constructs as its reflective indicators, and these first-order constructs are themselves measured using reflective manifest indicators (Jarvis et al., 2003, p. 204).

The Type I 'fit' models (Becker et al., 2012) used were examined in two stages[67]. First, a structural path model was estimated to test the internal consistency among the specified co-aligned first-order task and technology characteristics. This model was used to capture the main effects of these first-order factors on the TTF construct modelled as a second-order factor. Second, to comprehensibly examine the concept of 'fit' as covariation, a structural path model was estimated to test the second-order TTF construct for its effects on use and user performance. This model was used to fully capture and represent the covariation effects of 'fit' as a second-order factor.

The procedure used to model 'fit' is described as a 'repeated indicator approach'[68], where a higher-order latent variable is modelled by specifying a construct that represents all the manifest indicators of a set of underlying lower-order latent variables (Wold, 1982; Noonan and Wold, 1983; Lohmoller, 1989; Becker, Klein and Wetzels, 2012). As such, a

[66] It is recognized that in prior work, there have been inconsistencies in the modeling of a 'fit' as covariation, which should typically be modelled using reflective first-order, reflective second-order Type I models (Becker et al., 2012), in order to correctly observe the co-alignment among a set of observable underlying theoretically-related dimensions, in terms of a separate, unobservable construct (Venkatraman, 1990; Segars, 1994). Refer Section O.2 of Appendix O.

[67] In prior work, a baseline or direct (main) effects model, with no second-order 'fit' factor has also been specified for comparison with a 'fit' as co-alignment model subsequently specified, implying that each first-order factor directly impacts the criterion e.g. use or user performance (Venkatraman, 1989, p. 437). The modeled second-order factor 'fit' has been said to merely explain the covariation among the first-order factors more parsimoniously (Segars et al., 1998, p. 314). As such, the baseline model is not depicted in this chapter, as the focus is purely on internally consistent co-alignment 'fit' models, one specified without criteria variables, and one specified with effects on criteria variables i.e. use and user performance.

[68] The advantage of this approach is that it allows for the simultaneous estimation of all constructs simultaneously instead of estimating first-order and second-order dimensions separately (Becker et al., 2012, p. 365).

dual-purpose ‘fit’ as covariation model can be examined. By using this scheme, it is possible to capture the TTF construct as a second-order latent variable that consists of eight underlying inter-related task and technology characteristics as its first-order latent variables, each with their reflective manifest indicators, where this second-order latent variable is itself specified using all reflective manifest variables of its underlying first-order variables (Becker et al., 2012). Therefore in essence, the reflective manifest variables are used in the same model twice, first for the first-order latent variables, and second, for the second-order latent variables. Notably, the path coefficients between the first-order and second-order latent variables each must represent the loadings of the second-order latent variable (p. 365).

By evaluating a second-order factor model, it becomes possible to distinguish between the mere observation of first-order factors that are expressed as co-aligned and internally consistent reflective indicators of a second-order TTF factor, and the observation of its effects on a criterion variable or criteria variables as specified (Venkatraman, 1989). As such, the extent of a covariation ‘fit’ is only fully evident when its effects are observed. Of note, Venkatraman (1989) postulated that there are no directly observable indicators of this ‘fit’ construct represented as a pattern of co-aligned and internally consistent dimensions, arguing that instead, its meaning must be derived as a second-order factor through directly operationalized first-order factors, each with observable reflective indicators (p. 437). He further argued that the second-order factor can be termed as co-alignment, and observed that if first-order factors are consistent dimensions of a second-order factor, then it follows that all coefficients of first-order factor loadings of the second-order factor must be significant (p. 438). If these first-order factor loadings are statistically significant, then support for the existence of ‘fit’ as a second-order construct of co-alignment is established (Segars et al., 1998, p. 315). This postulation is further advanced in the present study. The co-alignment among first-order factors as the dimensions of a second-order factor is important to understanding the concept of internal consistency, and explaining the nature of a ‘fit’ as covariation. If the above-described conditions are satisfied, then covariation can be deemed an acceptable specification of ‘fit’, where its effects on a criterion variable or criteria variables are substantiated by the magnitude and significance of the relationship between the second-order factor and an observed outcome variable or set of variables (Venkatraman, 1989). Therefore, in the present study, a ‘fit’ as covariation can be represented as the appropriate co-alignment of task and technology characteristics that would impact use and user performance. As such, these characteristics are expressed as first-order factors examined as reflective indicators of a second-order factor 'fit', which is then tested for its subsequent impacts.

Coefficients of determination (R^2 values) of the endogenous constructs use and user performance were used to determine the predictive accuracy[69] of the estimated PLS structural path models (Hair et al., 2014, p. 174), and Stone-Geisser's Q^2 values (Geisser, 1974; Stone, 1974) of use and user performance were used to determine their predictive relevance[70] (Hair et al., 2014, p. 178).

Results of the structural path model estimates of TTF as Covariation are discussed in Section 9.5.

9.5 Results

9.5.1 The Testing of Fit as Internally Consistent Co-alignment

The following is a description of results following analysis of a reflective-reflective Type I[71] measurement model representing TTF tested for internally consistent co-alignment, per the following steps:

First, multiple regressions run to assess the collinearity[72] of the reflective first-order task and technology characteristics as reflective indicators (Hair et al., 2014, p. 124), yielded Tolerance values higher than 0.20 and VIF values lower than 5. Hence collinearity was not a problem (Hair et al., 2011).

Second, to substantiate a 'fit' as co-alignment and internal consistency, the significance of the paths from the reflective first-order task and technology characteristics as reflective

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[69] R^2 values of approximately 0.670, 0.333, and 0.190 are substantial, moderate, and weak, respectively (Chin, 1998; Urbach and Ahlemann, 2010, p. 21).

[70] A Q^2 value larger than zero for a certain reflective endogenous latent variable is indicative of its predictive relevance (Henseler et al., 2009, Hair et al., 2014, p. 178).

[71] The reflective measurement constructs of the first-order task and technology characteristics in the reflective-reflective Type I models specified were also tested for their internal consistency reliability (composite reliability), indicator reliability, convergent validity (average variance extracted), and discriminant validity (Hair et al., 2014, p. 97). Results are detailed in Tables O.1 to O.3 of Appendix O.

[72] Results of multi-collinearity assessment are shown in Table O.4 of Appendix O.

indicators of 'fit' as a second-order construct (outer weights), was assessed using a bootstrapping procedure (Hair et al., 2014, p. 132).

The structural path model estimated[73] to test *fit as co-alignment and internal consistency* is shown in Figure 9.2.

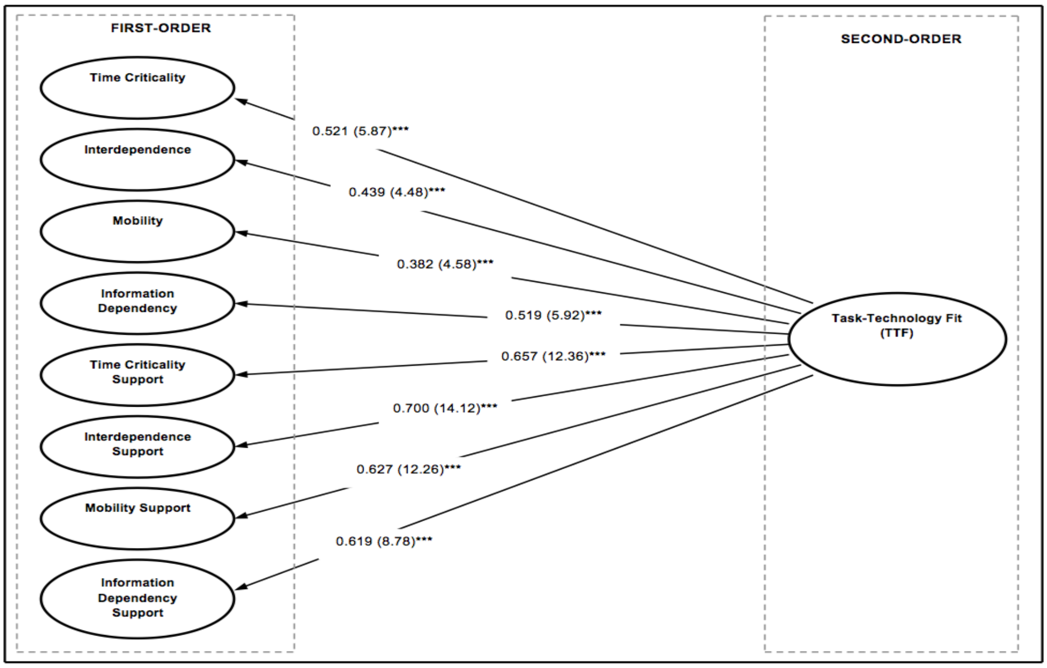

Figure 9.2. Path Model: Task-Technology Fit (TTF) as Internally Consistent Co-alignment

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals, of the structural main effects path model estimated to test *fit as co-alignment and internal consistency*, are shown in Table 9.1. Results indicate that the co-alignment of *time criticality* (path coefficient = 0.521, *t* = 5.87), *interdependence* (path coefficient = 0.439, *t* = 4.48), *mobility* (path coefficient = 0.382, *t* = 4.54), *information dependency* (path coefficient = 0.519, *t* = 5.92), *time criticality support* (path coefficient = 0.657, *t* = 12.36), *interdependence support* (path coefficient = 0.700, *t* = 14.12), *mobility support* (path coefficient = 0.627, *t* = 12.26), and *information dependency support* (path coefficient = 0.619, *t* = 8.78), has significant positive effects on fit ($p < 0.01$).

[73] Screenshots of the structural path model estimates representing fit as co-alignment and internal consistency, and its covariation effects, respectively, are shown in Figures O.1 and O.2 of Appendix O.

Table 9.1 Structural Path Model Results: The Main Effects of Fit as Co-Alignment and Internal Consistency					
Path	Path Coefficient (Outer Weight)	*t*	*p*	Significance	90% CI
Time Criticality ← Task-Technology Fit (TTF)	0.521	5.87	0.00	***	[0.47, 0.57]
Interdependence ← Task-Technology Fit (TTF)	0.439	4.48	0.00	***	[0.38, 0.50]
Mobility ← Task-Technology Fit (TTF)	0.382	4.54	0.00	***	[0.31, 0.45]
Information Dependency ← Task-Technology Fit (TTF)	0.519	5.92	0.00	***	[0.47, 0.57]
Time Criticality Support ← Task-Technology Fit (TTF)	0.657	12.36	0.00	***	[0.62, 0.69]
Interdependence Support ← Task-Technology Fit (TTF)	0.700	14.12	0.00	***	[0.66, 0.74]
Mobility Support ← Task-Technology Fit (TTF)	0.627	12.26	0.00	***	[0.59, 0.66]
Information Dependency Support ← Task-Technology Fit (TTF)	0.619	8.78	0.00	***	[0.57, 0.67]

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Therefore the internally consistent co-alignment among these co-aligned CHW task and mHealth tool technology characteristics was empirically substantiated. This internally consistent ‘fit’ as co-alignment was then tested for its covariation effects on use and user performance.

9.5.2 The Testing of Fit as Internally Consistent Co-alignment for Covariation Effects

The structural path model estimated to test *fit as internally consistent co-alignment* for covariation effects is shown in Figure 9.3. As depicted in Figure 9.3, the main effects model represented in Figure 9.2 as depicting internally consistent co-alignment, is extended and tested as a covariation model with which to examine TTF effects as a second-order factor on use and user performance outcomes. As alluded to in Section 9.4.2, this approach is evocative of Venkatraman (1989) who presented a schematic representation of the concept of covariation, by presenting two distinct models to highlight their core differences. More specifically, the first model signified a second-order ‘fit’ as co-alignment, depicted as a main effects model, while the second, described as the covariation model, captured the effects of this fit as co-alignment on use and user performance (p. 437).

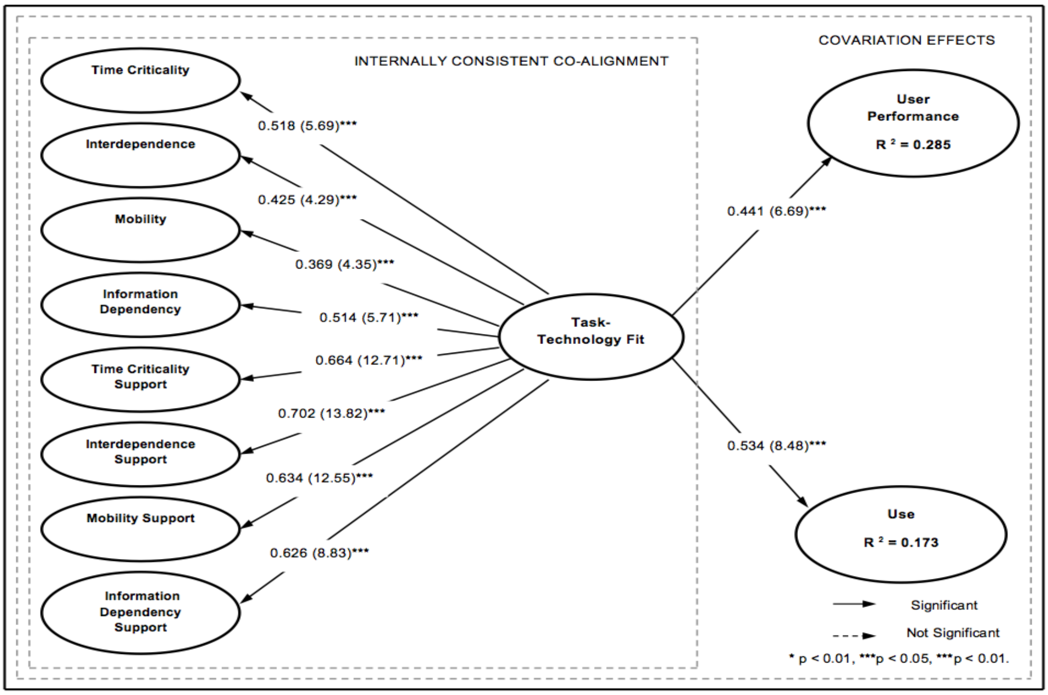

Figure 9.3. Path Model: The Covariation Effects of Task-Technology Fit (TTF) as Internally Consistent Co-alignment

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals, of the structural path model estimated to test *fit as co-alignment and internal consistency* for covariation effects are shown in Table 9.2.

Table 9.2 Structural Path Model Results: Covariation Effects

Path	Path Coefficient	*t*	*p*	Significance	90% CI
Time Criticality ← Task-Technology Fit (TTF)	0.518	5.69	0.00	***	[0.45, 0.58]
Interdependence ← Task-Technology Fit (TTF)	0.425	4.29	0.00	***	[0.36, 0.49]
Mobility ← Task-Technology Fit (TTF)	0.369	4.35	0.00	***	[0.31, 0.43]
Information Dependency ← Task-Technology Fit (TTF)	0.514	5.71	0.00	***	[0.45, 0.57]
Time Criticality Support ← Task-Technology Fit (TTF)	0.664	12.71	0.00	***	[0.62, 0.70]
Interdependence Support ← Task-Technology Fit (TTF)	0.702	13.82	0.00	***	[0.66, 0.75]
Mobility Support ← Task-Technology Fit (TTF)	0.634	12.55	0.00	***	[0.59, 0.68]
Information Dependency Support ← Task-Technology Fit (TTF)	0.626	8.83	0.00	***	[0.57, 0.68]
Task-Technology Fit (TTF) → Use	**0.441**	**6.69**	**0.00**	*****	**[0.33, 0.55]**
Task-Technology Fit (TTF) → User Performance	**0.534**	**8.48**	**0.00**	*****	**[0.43, 0.64]**

NS = Not Significant. *p < 0.10. **p < 0.05. ***p < 0.01.

Results in Table 9.2 indicate that TTF as the internal consistency of co-aligned CHW task and mHealth tool technology characteristics has significant positive covariation effects on *use* (path coefficient = 0.441, t = 6.69, p < 0.01) and *user performance* (path coefficient =

0.534, t = 8.48, $p < 0.01$). Thus ***Proposition 7 (P7)*** and ***Proposition 8 (P8)*** are supported. In addition, this fit model of internally consistent co-alignment has significant predictive accuracy for the endogenous constructs of *use* ($R^2 = 0.173$) and *user performance* ($R^2 = 0.285$), and significant predictive relevance for the endogenous constructs of *use* ($Q^2 = 0.100$) and *user performance* ($Q^2 = 0.163$).

9.6 Discussion

9.6.1 Fit as Internally Consistent Co-alignment

In this chapter, a 'fit' as co-alignment was specified among four CHW task and mHealth tool technology characteristics, and represented as a pattern of covariation among them. Findings indicate that this pattern was evident among the four mHealth tool technology and CHW task characteristics, supporting the inter-relatedness of these co-aligned factors, which is consistent with conceptualizations of TTF. In the context of CHW mHealth, a 'fit' signifies the appropriate co-alignment of the CHW task characteristics of time criticality, interdependence, mobility, information dependency and the mHealth tool technology characteristics of time criticality support, interdependence support, mobility support, and information dependency support, that will influence use and user performance. This observed co-alignment of internally consistent mHealth tool support functions to CHW task needs is consistent with Venkatraman and Prescott's (1990) notion of 'fit' as the simultaneous, holistic configuration of a set of inter-related components (p. 5). Initially, based on the postulations of Venkatraman (1989), the internal alignment among CHW task and mHealth tool dimensions was conceptualized and found to be a construct that represents internal consistency. From this perspective of 'fit', it is evident that internal consistency must be formally represented in a TTF model (Figure 9.3), in order for use and user performance effects to be directly assessed. The findings adduced corroborate Bergeron, Raymond and Rivard's (2001) observation that 'fit' is a pattern of internal consistency among a set of underlying and theoretically related variables (p. 135). Wang, Shih, Jiang, and Klein (2008) similarly observed that the internal co-alignment of consistent ERP factors had significant positive impacts on implementation success (p. 1618). Findings clearly indicate that the co-variation among the mHealth tool's support functions and CHW task needs is positively associated with both use and user performance. This means that in context, internally consistent, concurrent mHealth tool support for the CHW task needs of time criticality, interdependence, mobility, and information dependency, would result in higher levels of dependence on technology use and CHW performance. It is therefore evident that the alignment of mHealth tool support functions to CHW task needs has positive technology use and user performance consequences. As envisioned by Venkatraman (1989), 'fit' represents the central thread or internal logic that underlies the inter-relatedness of a set of factors empirically evaluated for their degree of covariation (Venkatraman, 1986, p. 436).

9.6.2 Implications for Research

There are four emergent implications for research arising from the findings discussed in this chapter.

First, findings constitute new empirical insights into the conceptualization of TTF, and assessment of its effects on use and user performance in a context-specific domain. Specifically, conceptualizing TTF as a pattern of covariation offers the advantage of simultaneously evaluating a 'fit' between multiple first-order constructs as reflective indicators of a second-order 'fit' construct that is linked to the outcomes of use and user performance. As evidenced by the results reported in this study, this represents a transition from the observation of internally consistent co-alignment, to the examination of its covariation effects on use and user performance. Therefore to ensure conceptual and schematic clarity, and simplify the evaluation of 'fit' as covariation, the concepts of internally consistent coalignment must be more precisely examined using such a phased approach. This is significant because contrary to basic assumptions, a 'fit' as internally consistent co-alignment can be differentiated from its covariation effects. If the internally consistent co-aligned first-order factors are considered on their own, the significance of their path coefficients as factor loadings of a second-order factor 'fit' construct are established. If covariation is considered on its own, the significant effects of this second-order factor 'fit' construct on use and user performance are evidenced. This sequenced evaluation of the covariation 'fit' perspective represents a relatively unique approach to evolving TTF research. This is a subtle distinction that to date, has not been succinctly explained in prior 'fit' research, and as such, is clearly explicated and clarified in the present study.

Second, it is important to emphasize that in light of reported findings, just examining the direct effects of co-aligned task and technology characteristics, is insufficient for discerning the full extent of a pattern of covariation between them. When these co-aligned characteristics are, however, examined for an internally consistent 'fit' and its subsequent effects on use and user performance, their covariation becomes observable, thereby offering a more complete picture. In essence, a 'fit' as covariation is not directly observable, such that its presence must be tested for in order for it to manifest. This is consistent with Venkatraman's (1989) postulation that the co-variation among co-aligned factors is observed at a higher theoretical plane than these factors, which are essentially the underlying dimensions of the 'fit' between them. In other words, 'fit' is an unobservable construct specified as coalignment, and its meaning is derived through first-order factors measured using observable reflective manifest indicators (Bergeron, Raymond and Rivard, 2001, p. 437). Thus the effective application of this principle to TTF research is justified, as evidenced in this chapter.

Third, in light of the empirical evidence of internally consistent co-alignment, TTF researchers can better understand and explain the nature of a 'fit' between a set of inter-related, underlying task and technology characteristics. These characteristics are essentially critical success factors that are observed in a single model capturing their coherence in a single theoretical model. This approach represents an effective way in which researchers can directly measure and observe whether a set of co-aligned factors are consistent, coherent first-order contributors of TTF represented as a second-order factor. In essence, by using a reflective-reflective Type I model (Becker et al., 2012) in which main effects and covariation effects are distinguishable, the concept of a 'fit' as covariation is better explicated and more succinctly expressed.

Fourth, it is empirically evident as demonstrated in this chapter, that contrary to widespread notions, internally consistent co-alignment and covariation effects can be differentiated, as the transition from the former to the latter has been empirically demonstrated in this study. As has been established in this chapter, there appears to be a sequence through which a preceding 'fit' as co-alignment can be examined for its covariation effects. In other words, inter-related components as lower-order factors that are in co-alignment must significantly constitute a 'fit' as a higher-order factor, for their internal consistency to be empirically substantiated. For covariation as an observable pattern to be grasped in its entirety, it is imperative that this internally consistent ‘fit’ as co-alignment is then examined for its effects on criteria variables such as performance. Findings indicate that researchers must not make the erroneous assumption that an internally consistent first-order ‘fit’ between a set of co-aligned first-order factors, and the testing of its covariation effects, are necessarily identical states, and must instead recognize that the evaluation of a ‘fit’ as covariation is in fact sequential, thus necessitating a phased approach. This signifies a richer understanding of the ‘fit’ perspective of covariation. In the manner described, the observation of a pattern of covariation can be considered more credible, thereby enhancing ones understanding of ‘fit’ as covariation. This further lends credence to using a ‘two-stage approach’ as an effective supplement to second-order factor analysis techniques. In essence, the establishment of internal consistency need not merely be an end in itself. As such, researchers ought to further examine an internally consistent ‘fit’ as co-alignment for its effects on a set of specified criteria variables.

9.6.3 Implications for Practice

There are two implications for practice arising from the findings discussed in this chapter.

First, in designing technologies that ‘fit’ the task requirements of users, practitioners must strive to establish a balance between mHealth tool support functions and CHW task needs. If a technology function-user need ‘fit’ is best captured as a pattern of consistent and concurrent resource allocations in the form of an mHealth tool’s support for the CHW task needs of time criticality, interdependence, mobility, and information dependency, then any one particular task or technology characteristic is by itself insufficient for optimal use and user performance levels to be attained. Thus sufficient attention must be afforded to all task and technology characteristics so as to maximize use and user performance. Therefore, it can be recognized that the characteristics of the CHW task and mHealth tool can be joined together in a holistic configuration that signifies their coherence in a shared user environment, thereby achieving a state of completeness. In other words, a pattern or stream of user needs and tool functions, all of which must be prioritized, are expected to coherently constitute a ‘fit’ pattern that would in turn impact levels of use and user performance output. As such, in a given context, designers must allocate adequate resources to all user need and tool functions, to effectively attain and reinforce a ‘fit’ as the co-existence of these components in co-alignment.

Second, findings can constitute empirical evidence with which practitioners can determine technology use and user performance impacts as a function of the level of coherence between concurrent CHW task and mHealth technology characteristics. Moreover, with this evidence-based approach as a diagnostic framework, quantifiable benchmarks can be determined and used to calibrate those levels of coherence that are necessary for the optimization of use and task performance in particular contexts. Practitioners would be able to effectively determine the degree of internal consistency among a set of co-aligned inter-related user needs and tool functions, so as to create decision streams that are explicitly informed by the relative weighted significance of these factors, to better interpret use and user performance levels.

9.7 Chapter Conclusion

The purpose of this chapter was to adapt Venkatraman’s (1989) Fit as Covariation perspective to test the effects of Task-Technology Fit (TTF) on mHealth tool use and CHW performance. An observable pattern of co-aligned, internally consistent CHW task and mHealth technology characteristics was examined for its covariation effects on use and user performance. This co-alignment and internal consistency of task and technology characteristics was found be significant, therefore establishing a ‘fit’. This ‘fit’ as co-alignment and internal consistency was found to have positive impacts on use and user performance. These results indicate that ‘fit’ as an observable pattern of co-aligned, internally consistent task and technology characteristics, will lead to increased levels of CHW dependence on the mHealth tool, and the more effective and efficient delivery of higher quality patient care. As such, the effects of a TTF pattern as an observed state of covariation were empirically substantiated.

Results of tests of TTF as Covariation and its impacts on use and user performance are summarized in Table 9.3.

Table 9.3. Findings		
	Proposition	Finding
P7	Fit as the internally consistent co-alignment of task (need) and technology (function) characteristics will influence use.	Supported
P8	Fit as the internally consistent co-alignment of task (need) and technology (function) characteristics will influence user performance.	Supported

In Chapter 9, TTF as Covariation and its effects on use and user performance was examined. In Chapter 10, the determinants of use and its effects on user performance are examined.

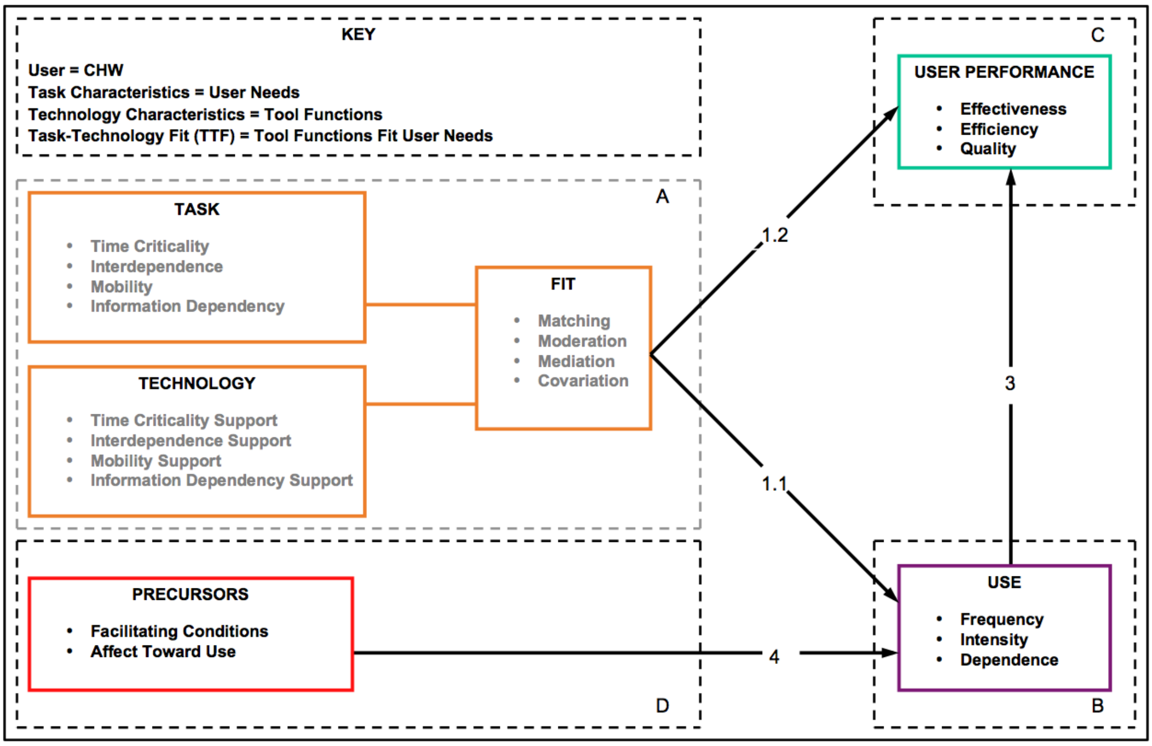

Figure 9.4. Use, Task-Technology Fit (TTF), Precursors, and User Performance

10 The Determinants of Mobile-Health (mHealth) Tool Use and Effects on User Performance

10.1 Introduction

In Chapter 1, it was noted that there is a dearth of evidence on the impact of mHealth tool use on CHW user performance. Moreover, it was recognized that there is limited knowledge of the determinants of mHealth tool use (Liu et al., 2011). Consequently, to address this knowledge gap, research questions, 5, 6, and 7, were formulated:

5. What are the determinants of mHealth tool use by CHWs?
6. To what extent do these determinants impact mHealth tool use by CHWs?
7. How does mHealth tool use impact CHW performance?

The purpose of this chapter is to address these three questions. In the conceptual model developed in this chapter, use is positioned as mediating between a set of precursors and user performance. The theoretical underpinnings of this conceptual model are discussed in Sections 10.2 and 10.3.

10.2 Task-Technology Fit (TTF) and the Technology-to-Performance Chain (TPC)

As articulated in Chapter 4, the basic 'Fit-Focus' model of TTF was theorized to influence use and user performance outcomes. However, in that original TTF model, use as an outcome was not linked to performance. Thus for an improved understanding of user performance, the inclusion of use impacts has been proposed (Goodhue and Thompson, 1995, p. 214). 'Fit' can thus be linked to user performance through use. The extended theoretical TTF model is depicted in Figure 10.1. In this 'Fit-Focus' TTF model, the extension representing a link between use and user performance is highlighted. This extension of the TTF model completes a TPC that links technology to user performance through a 'fit' with the task and its use. However, TTF is the core process through which technology impacts user performance. As such, TTF theory underpins this

TPC. Within this TPC, use is a function of ‘fit’. However, use also has additional determinants or precursors that must be considered.

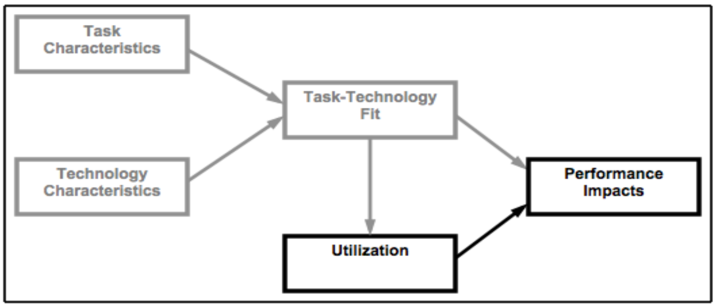

Figure 10.1. Extended ‘Fit-Focus’ Task-Technology Fit (TTF) Model (Goodhue and Thompson, 1995, p. 220)

10.3 Technology Use and its Precursors

In Chapter 4, it was also observed that use is behavioural and considered to have determinants other than a ‘fit’ between the task and technology. These additional determinants are underpinned by theories of use (Fishbein and Azjen, 1975; Bagozzi, 1982). Thus the completed TPC can be extended to include precursors as additional determinants of use, where theories of use are drawn on to provide a relevant underpinning. Within this extended TPC, use is positioned between its determinants and consequent user performance.

Trice and Treacy (1986) argued that linkages between utilization and its determinants needed to be better understood. Davis (1989) observed that drivers of system user behaviour should be investigated through the critical examination of alternative theories and models for predicting utilization. Central to these theories, user attitudes and beliefs are fundamental to understanding system utilization (Lucas, 1975, 1981; Robey, 1979; Cheney, Mann and Amoroso, 1986; Swanson, 1987; Davis, 1989; Davis, Bagozzi and Warsaw, 1989). As postulated in Chapter 4, use is considered to have determinants besides a ‘fit’ between the task performed and the IT used. In prior works, determinants of IT use have been underpinned by theories of Attitude and Behaviour (Fishbein and Azjen, 1975; Azjen and Fishbein, 1977; Triandis, 1979). The first of these reference theories is previewed next.

10.3.1 The Theory of Reasoned Action (TRA) and The Theory of Planned Behaviour (TPB)

The Theory of Reasoned Action (TRA) is based on the premise that individuals evaluate outcomes of specific behaviour and form intentions based on their evaluations (Fishbein and Azjen, 1975). These intentions influence the intended behaviour (p. 372). The TRA model was extended to form the Theory of Planned Behaviour (TPB). The TPB is based on the premise that 'behavioural, normative, and control beliefs' influence the three factors of 'attitude toward behaviour', 'subjective norm', and 'perceived behavioural control'. These factors in turn determine intention and subsequent behaviour (Azjen, 1985; 1991). The TPB model, an extended TRA model, is depicted in Figure 10.2.

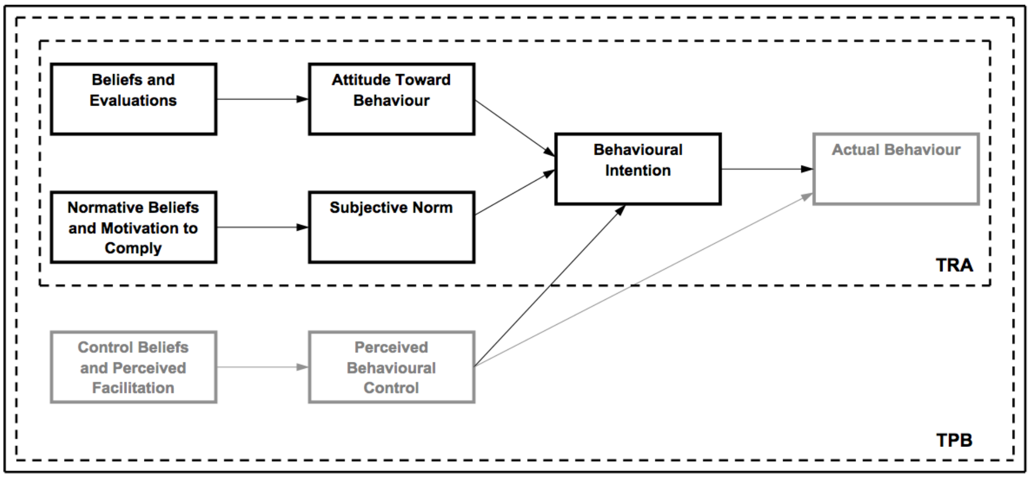

Figure 10.2. The Theory of Planned Behaviour (TPB) (Azjen, 1985)

As depicted, the constructs of 'control beliefs and perceived facilitation', and 'perceived behavioural control', were included to extend the TRA model (Figure 10.2). The TRA and TPB informed Bagozzi's (1982) Expectancy-Value Theory, discussed next.

10.3.2 Expectancy-Value Theory

Expectancy-Value Theory is based on Fishbein and Azjen's (1975) TRA and TPB (Azjen, 1985, 1991), in conjunction with Triandis' Interpersonal Behaviour model (1979, 1980). A fundamental difference between the TRA, TPB, and Interpersonal Behaviour model, is the presence of the construct of 'affect'. This construct is not included in the TRA and TPB models. In these models, 'attitude' is included as an outcome of cognitive evaluations of behavioural consequences (Fishbein and Azjen, 1975). In contrast, Triandis (1979) included 'affect', which was considered to occur 'in the moment', and independent of beliefs of behavioural consequences. Subsequently, Bagozzi (1982) developed the ‘Volitional Model’ incorporating the concepts of TRA, TPB, and Interpersonal Behaviour. This conceptual model is depicted in Figure 10.3.

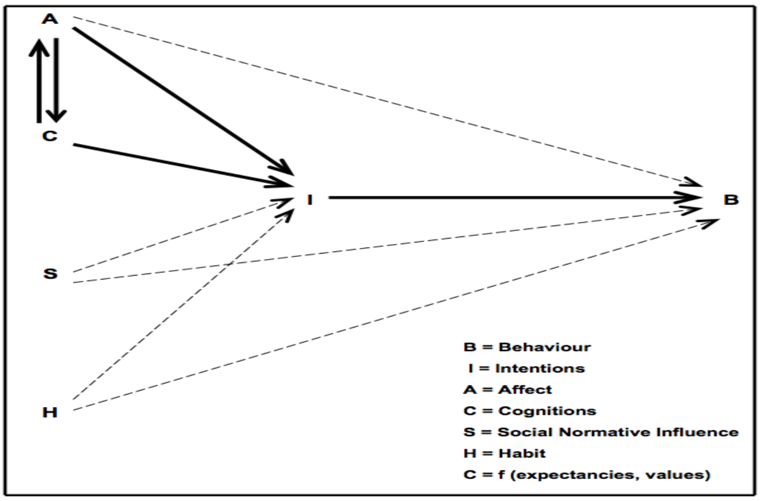

Figure 10.3. The Volitional Model (Bagozzi, 1982, p. 581)

This model was adapted and used to theorize the relationship between a set of precursors and IT use, and depicted as the lower portion of Goodhue’s (1992) System-to-Performance Chain (Figure 10.4). These precursors were considered as determinants of IT use besides a ‘Task-System Fit’. In addition to behavioural consequence beliefs and affect, ‘social norms’ and ‘habit’ have been considered to affect behaviour (Bagozzi, 1982). However, despite potential impacts of ‘social norms’ and ‘habit’ as determinants of IT use, these constructs have not been recognized as user evaluations of systems, and are thus not typically considered (Goodhue, 1992).

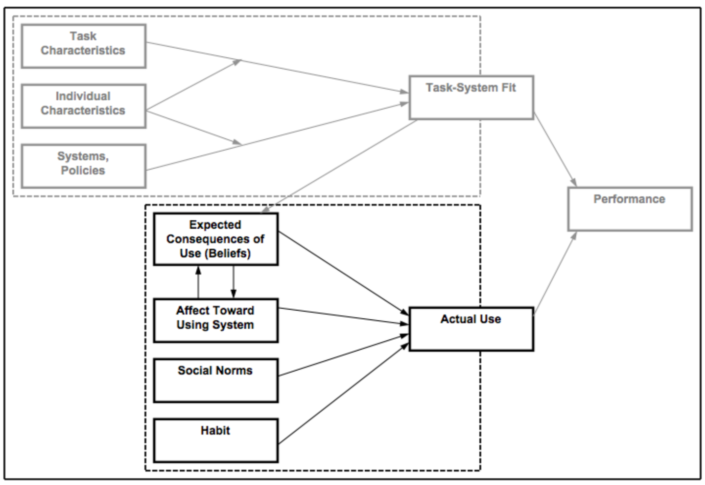

Figure 10.4. Bagozzi’s (1982) Model in Goodhue’s (1992) System-to-Performance Chain

Goodhue and Thompson (1995), and Goodhue (1997), also incorporated Bagozzi's (1982) model into TPCs to examine precursors of use as determinants other than TTF. Notably, in these TPCs, 'facilitating conditions' was included as a precursor of use. Triandis (1980) described 'facilitating conditions' as objective factors that make an act easy to do (p. 205). In previous IS research, 'facilitating conditions' have been described as those supportive factors in the environment that simplify the use of ITs (Thompson et al., 1991). For example, the provision of technical support for users is one example of a facilitating condition that could influence the use of ITs in task performance (p. 129). 'Facilitating conditions' have also been variously described in terms of 'perceived behavioural control', defined as the IT user's perceived internal and external constraints on behaviour, such as efficacy, resources, or technology as an enabler (Taylor and Todd, 1995a, 1995b). Drawing on the above, this chapter's conceptual model is developed in Section 10.4, next.

10.4 Conceptual Model

As discussed in Section 10.3, the precursors of 'affect' and 'facilitating conditions' are important determinants of IT use. Unlike 'attitude' (Fishbein and Azjen, 1975), 'affect' (Triandis, 1979) can impact use directly, and not through 'behavioural intentions'. 'Facilitating conditions' are considered important because actual usage behaviour is not possible if objective conditions in the environment prevent it (Triandis, 1980). As articulated in Section 10.3, 'social norms' and 'habit' do not represent user evaluations of systems. As such, these precursors of use are not considered as complementary to TTF. 'Expected consequences' could complement TTF, but has been positioned as a conduit through which use is influenced (Goodhue and Thompson, 1995). Previously, Triandis (1980) modelled a 'perceived consequences' construct to impact intentions and subsequent behaviour. Goodhue (1997) asserted that in the IT domain, the prediction of actual behaviour and subsequent performance impacts is of more significance than the determination of intentions. This approach was consistent with prior studies of IT use (Davis, 1989; Thompson et al., 1991; Moore and Benbasat, 1992). As such, intentions were omitted from their TTF-influenced conceptual model (p. 450). TTF could be examined for its direct impacts on use. Notably, determinants independent of TTF that directly impact use are considered, and as such, perceived consequences of use are not included in the model for the present study.

Affect toward use and perceived facilitating conditions that enable use are of potentially greater relevance. Thus the factors of ‘affect toward use’ and ‘facilitating conditions’ are most appropriate to a TPC model. Use is an outcome of both these precursors and TTF, and a determinant of user performance. A conceptual model is thus developed linking use as an outcome of TTF, to precursors, and subsequent user performance. This model is depicted in Figure 10.5.

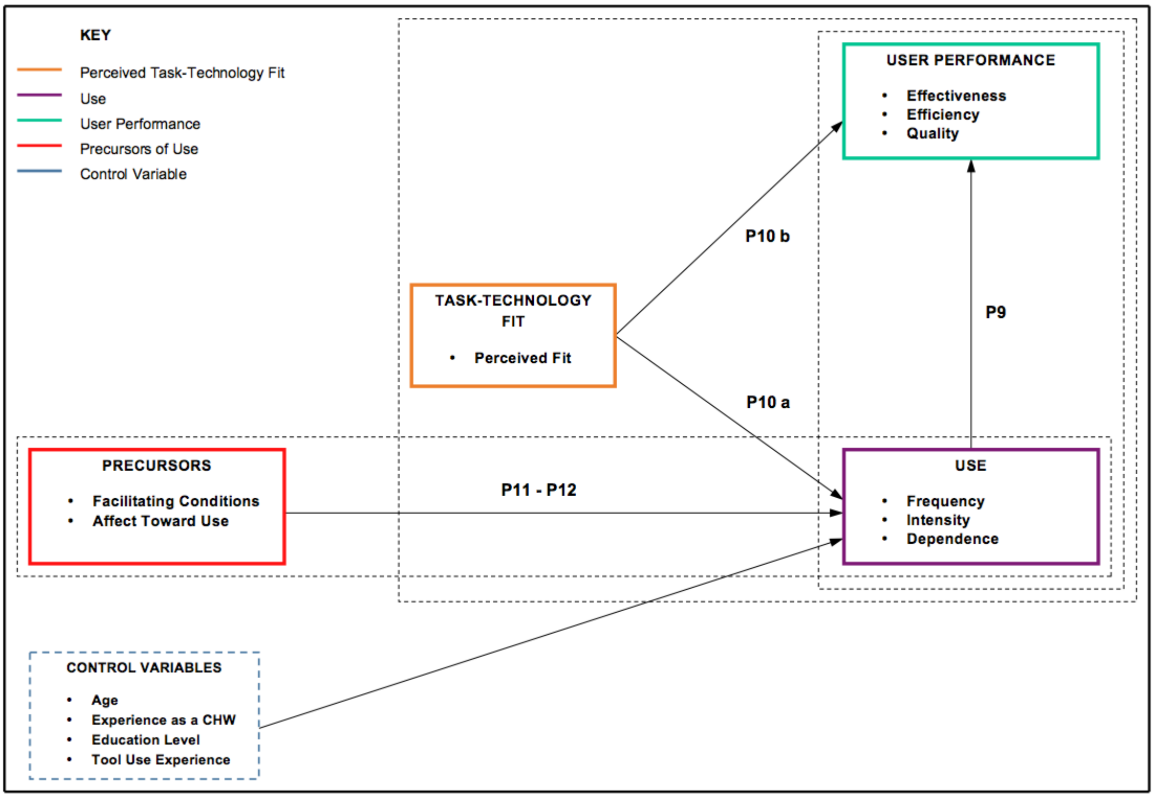

Figure 10.5. Conceptual Model: Extended Technology-to-Performance Chain (TPC)

Use is conceptualized as the ‘frequency’, ‘intensity’, and ‘dependence’ with which the technology user uses the tool or system (Lee, 1986; Goodhue and Thompson, 1995; Igbaria et al., 1997; Lee et al., 2003; McGill and Hobbs, 2007; Teo and Men, 2008; Junglas et al., 2009). First, *frequency* is how many times on average the user uses the technology in task performance (Lee, 1986; Lee et al., 2003; Teo and Men, 2008). The repetitive use of ITs, i.e. enhanced user frequency, signifies this regularity (Raymond, 1985; Hou, 2012). Second, *intensity* is the amount of time spent using the technology in task performance (Lee, 1986; McGill and Hobbs, 2007). In the early learning phase for many users, more time would typically be spent using the technology. However, the intensity of technology use may decrease as the user becomes more proficient at using the tool or system (Szajna, 1993; Igbaria et al., 1997). Third, *dependence* is the extent to which the user has come to rely on using the technology in task performance (Junglas et al., 2009). The integration of ITs into individual work routines has been observed to enhance user dependence (Goodhue and Thompson, 1995).

User performance is reflected as the effectiveness, efficiency, and quality, with which tasks are completed or executed using the technology (Garrity and Sanders, 1998; Torkzadeh and Doll, 1999; Belanger et al., 2001; Staples and Seddon, 2004; Teo and Men, 2008; Junglas et al., 2009). First, *effectiveness* is the execution of actions or tasks to achieve desired work outcomes or results (Teo and Men, 2008). ITs have been observed to improve the effectiveness of users by enhancing their productive output in executing tasks (Torkzadeh and Doll, 1999). Second, *efficiency* is the completion of tasks in the least time, at the lowest cost (Garrity and Sanders, 1998). ITs have been observed to improve the efficiency of users by automating time-consuming tasks, thereby reducing the wastage of resources (Belanger, Collins and Cheney, 2001). Third, *quality* is the completion of tasks without committing errors (Junglas et al., 2009). ITs have been observed to improve output quality not only by validating the inputs of users, but also minimizing errors in the capture and transmission of data (Belanger et al., 2001).

In order to complete a TPC, the TTF outcome of use is linked to user performance (P9). As per TTF theory (Goodhue 1995; Goodhue and Thompson, 1995; Dishaw, 1994; Dishaw and Strong, 1998a; Strong et al., 2006), 'fit' is linked to use (P10a) and user performance (P10b). For purposes of this chapter, TTF is conceptualized as 'perceived fit'. 'Perceived fit' is the perception of the intended user that the technology used meets user task requirements (Pendharkar et al., 2001; Jarupathirun and Zahedi, 2007). As a point of departure from the conceptualizations tested in Chapters 6 to 9, 'fit' in this chapter is conceptualized purely as perceptual, comprising multiple user-evaluated TTF dimensions. This is evocative of Goodhue and Thompson's (1995) TTF as User Evaluation (UE), and Dishaw and Strong's (1998b) TTF as Fitness-For-Use manifestations, comprising multiple user-perceived 'fit' dimensions in a singular construct. Goodhue (1992b) observed that TTF can be measured independently of task and technology antecedents, and therefore forming a basis for a more 'general fit' as opposed to 'a specific (derived) fit' (Dishaw, 1994, p. 63). This more general 'fit' has been proven an acceptable alternative TTF concept, operationalized for subsequent testing.

As per Expectancy Value Theory (Triandis, 1979, 1980; Bagozzi, 1982) and its antecedents the TRA (Fishbein and Azjen, 1975) and TPB (Azjen, 1985, 1991), the precursors of facilitating conditions and affect toward use are linked to technology use (P11, P12). First, *facilitating conditions* are support factors in the user environment that are conducive to technology use (Thompson et al., 1991). For example, supporting resources e.g. user training, have been observed to facilitate the use of ITs (McGill and Hobbs, 2007). Second, *affect toward use* is the extent to which the user has a liking for the technology (Compeau, Higgins and Huff, 1999). The positive affect of users towards use e.g. enjoyment, is expected to enhance the use of ITs. However, the negative affect of users e.g. apprehension, could undermine their use of ITs (McGill and Klobas, 2009). The model's propositions are developed further below.

10.4.1 The Link between Use and User Performance

The use or non-use of technology can impact user performance. If the technology is well designed, then its increased use should positively impact user performance. However, the non-use of technology that is well designed should negatively impact user performance (Staples and Seddon, 2004). This is because any supposed gains in the effectiveness and efficiency of the user are lost due to non-use of the technology (p. 22). The positive linkage between use and user performance is considered a key component of the TPC, and has been examined in several studies (Goodhue and Thompson, 1995; Goodhue et al., 1997; D'Ambra and Wilson, 2004b; McGill and Klobas, 2009). The enhanced use of the technology should lead to an increase in user performance (McGill et al., 2011). In order for technology to have an impact on user performance, it must be used (Teo and Men, 2008). The use of mHealth tools by CHWs is expected to positively impact their performance of tasks. Moreover, a dependence on frequent and intensive use of mHealth tools would lead to more effective and efficient patient care, with improved quality. To examine the link between use and user performance, the following proposition is formulated:

Proposition 9 (P9): *The use of mHealth tools by CHWs will positively influence user performance.*

10.4.2 The Link between Task-Technology Fit (TTF) and Use and User Performance

In accordance with TTF theory, the ‘fit’ between the task and the technology, is hypothesized to influence both use and user performance (refer Chapters 6 to 9). As such, if users perceive a closer ‘fit’ between their needs and the functionality of the technology used, they then believe that the technology is useful, affords greater relative advantage in the completion of tasks, or enhances their productivity (Goodhue, 1997). This is consistent with the notion that a ‘fit’ between task and technology represents an assessment of how satisfactorily tool functions meet user needs (p. 452). In prior works, the positive linkage between TTF and use has been suggested (Goodhue and Thompson, 1995; Dishaw and Strong, 1998a, 1998b). If users expect that the technology used represents the capacity needed to complete the required tasks, then higher use should ensue (Teo and Men, 2008). If the technology used is ‘fit’ for user needs, then it should positively impact technology use. This is because the user considers the technology most appropriate for the required task (McGill et al., 2011, p. 48). In past studies, a positive linkage between TTF and user performance has also been observed (Goodhue, 1995; Goodhue et al., 1997; Goodhue, Klein and March, 2000; D’Ambra and Wilson, 2004a, 2004b). If users expect that required tasks can be completed using the appropriate technology, then higher performance should result (Staples and Seddon, 2004). If the technology used is ‘fit’ for user needs, then it should positively impact task performance. This is because the user considers the technology more useful for completing the required task (p. 21). A perceived ‘fit’ between CHW user task needs and mHealth tool technology functions will lead to improved use and user performance. Thus CHWs would become highly dependent on using the mHealth tool frequently, with a high degree of intensity, and delivering higher quality patient care more effectively and efficiently.

To examine the link between TTF and use and user performance, the following propositions are formulated:

Proposition 10a (P10a): *The perceived 'Fit' between CHW tasks and mHealth tools will positively influence use*.

Proposition 10b (P10b): *The perceived 'Fit' between CHW tasks and mHealth tools will positively influence user performance*.

10.4.3 The Link between Precursors of Use and Use

In prior works, the linkage between beliefs and affect, and user behaviour, has been observed (Hartwick and Barki, 1994). In the IT domain, user behaviour has been observed to be instrumental to task performance (Goodhue, 1997). The affect of users toward the technology used influences this usage behaviour (Staples and Seddon, 2004, p. 22). In addition to the affective response of users, situational factors such as 'facilitating conditions' could enable the use of the technology to perform tasks (Goodhue et al., 1997, p. 97). These factors are considered external and could also constrain technology users in their task performance (Goodhue, 1997, p. 451). Therefore for use to occur, users must have a positive affect toward the technology used. In addition, their enabled technology use for the performance of tasks must be facilitated (Thompson et al., 1991). The resource facilitation of CHWs in low-resource settings is useful for their performance (Braun et al., 2013). Moreover, these CHWs must be sufficiently motivated to deliver improved patient care during household visits (Bhattacharya et al., 2001). If CHWs perceive that there are resources that facilitate their support, and have a liking for, or positive inclination towards mHealth tools, then they would become more frequent technology users with higher levels of intensity, and higher use dependence.

To examine the link between the precursors of 'affect toward use' and 'facilitating conditions' and use, the following propositions are formulated:

Proposition 11 (P11): *Affect toward use will positively influence mHealth tool use.*

Proposition 12 (P12): *Facilitating conditions will positively influence mHealth tool use.*

The methods used to test the conceptual model (Figure 10.6) are discussed in Section 10.5.

10.5 Methods

10.5.1 Sampling, Instrument, and Measures

Dataset 1 (n = 201) is used in this chapter. Dataset 1 is detailed in Section B.1 of Appendix B. The dataset comprises responses from CHW mHealth tool users in the Siaya, Nandi, and Kilifi counties. A structured questionnaire survey instrument was used to collect data. The measures for perceived fit, use, user performance, and precursors of use, were developed as described in Appendix E. These constructs were tested for multi-collinearity, reliability and validity, and final measures were used in subsequent analyses as per the procedures and criteria outlined in in Sections G.1 and G.2 of Appendix G.

The use dimensions of frequency, intensity, and dependence, were captured using self-reported measures. First, a measurement scale adapted from Thompson, Higgins and Howell (1991), was used to measure *frequency*. *Frequency* was measured on a scale from 1 = almost never to 7 = several times a day. Second, a measurement scale adapted from Igbaria, Zinatelli, Cragg and Cavaye (1997), was used to measure *intensity*. *Intensity* was measured on a scale from 1 = almost never to 6 = more than 3 hours. Third, a three-item measurement scale adapted from Junglas, Abraham and Ives (2009), was used to measure *dependence*. *Dependence* was measured on a seven-point Likert scale from 1 = strongly disagree to 7 = strongly agree. The items used to measure these self-reported use dimensions are summarized in Table 10.1.

Table 10.1. Measurement Items for Use

Item	Statement	Dimension			Source(s)
		Frequency	Intensity	Dependence	
1 [a]	On average, how many times do you use the mHealth tool to perform your tasks?	✓			Thompson et al., (1991)
1 [a]	On average, how much time do you spend per day using the mHealth tool to perform your tasks?		✓		Igbaria et al., (1997)
1 [b]	I am very dependent on the mHealth tool to perform tasks.			✓	Junglas et al., (2009)
2 [b]	My work is dependent on using the mHealth tool to perform tasks.			✓	
3 [b]	Using the mHealth tool allows me to do more than would be possible without it.			✓	

a = Measured on 7-point scale 1 = Almost Never to 7 = Several Times a Day

b = Measured on 6-point scale 1 = Almost Never to 7 = More than 3 hours

The use precursor dimensions[74] of facilitating conditions and affect toward use were also captured using self-reported measures. First, a four-item measurement scale adapted from Taylor and Todd (1995) was used to measure *facilitating conditions*. Second, a five-item measurement scale adapted from Compeau and Higgins (1995) and Compeau, Higgins and Huff (1999) were used to measure *affect toward use*. *Facilitating conditions* and *affect toward use* were measured on seven-point Likert scales from 1 = strongly disagree to 7 = strongly agree. The items used to measure these self-reported use precursor dimensions[75] are summarized in Table 10.2.

Table 10.2. Measurement Items for Precursors of Use				
Item	Statement	Dimension		Source(s)
		Facilitating Conditions	Affect Toward Use	
1 [a]	I have the resources required to use the mHealth tool.	✓		Taylor and Todd (1995)
2 [a]	I have the knowledge required to use the mHealth tool.	✓		
3 [a]	With the required training, it would be easy for me to use the mHealth tool.	✓		
4 [a]	The mHealth tool does not complement paper-based systems I use.	✓		
1 [a]	I like using the mHealth tool.		✓	Compeau and Higgins (1995), Compeau, Higgins and Huff (1999)
2 [a]	I look forward to using the mHealth tool.		✓	
3 [a]	Using the mHealth tool is frustrating (R).		✓	
4 [a]	Once I start using the mHealth tool, I find it hard to stop (R).		✓	
5 [a]	I get bored quickly when using the mHealth tool.		✓	

a = Measured on 7-point scale 1 = Almost Never to 7 = Several Times a Day

R = Reverse Scored

Perceived TTF was measured as detailed in Appendix E as a sixteen-item measurement scale adapted from Dishaw (1994) and Junglas et al. (2009). Items such as 'the [tool] supports me in receiving information from co-workers' (Junglas et al., 2009) were used to measure perceived TTF. A more detailed outline of these measures is provided in Section E.1 of Appendix E.

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[74] Item 4 of the precursor 'facilitating conditions', and items 3, 4, and 5 or the precursor 'affect toward use' were excluded, as they did not meet the criteria for internal consistency reliability and convergent validity criteria (Hair et al., 2014, p. 107) as detailed in Table G.7 of Appendix G.

[75] The proposed link between precursors of use and use was positive. Thus the negatively phrased survey instrument items 3 and 5 of the precursor 'affect toward use' were reverse scored to ensure that all correlations and loadings were aligned within the same factor (Hair et al., 2010).

User performance was measured as detailed in Section 3.3 of Chapter 3, and Appendix E as an eight-item measurement scale adapted from Torkzadeh and Doll (1999), Junglas et al. (2009), and Hou (2012). Items such as 'the [tool] increases my productivity' (Torkzadeh and Doll, 1999) were used to measure user performance.

Partial Least Squares - Structural Equation Modeling (PLS - SEM) was used to test the effects of (1) use on user performance, (2) perceived TTF on use and user performance, and (3) precursors of use on use. A structural path model was estimated to test these effects. Coefficients of determination (R^2 values) of the endogenous constructs use and user performance were used to determine the predictive accuracy[76] of the estimated PLS structural path model (Hair et al., 2014, p. 174), and Stone-Geisser's Q^2 values (Geisser, 1974; Stone, 1974) of use and user performance were used to determine their predictive relevance[77] (Hair et al., 2014, p. 178). In addition, f^2 (q^2) effect sizes were computed to determine the relative impacts of use, perceived TTF, and precursors of use, on the predictive accuracy (R^2) and relevance (Q^2) of the estimated PLS structural path model (Urbach and Ahlemann, 2010; Hair et al., 2014).

Use was positioned as an intervening mechanism between (1) perceived TTF and user performance, and (2) precursors and user performance. As such, PLS mediator analyses with bootstrapping (Preacher and Hayes, 2004) were used to test use for mediating effects.

10.6 Results

10.6.1 Main Effects

The structural path model estimated to test the effects of (1) use on user performance, (2) perceived TTF on use and user performance, and (3) precursors of use on use, is shown in Figure 10.6. The model has significant predictive accuracy for the endogenous constructs of *use* ($R^2 = 0.318$) and *user performance* ($R^2 = 0.490$). The model also has significant predictive relevance for the endogenous constructs of *use* ($Q^2 = 0.117$) and *user performance* ($Q^2 = 0.281$).

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[76] R^2 values of approximately 0.670, 0.333, and 0.190 are substantial, moderate, and weak, respectively (Chin, 1998; Urbach and Ahlemann, 2010, p. 21).
[77] Q^2 values larger than zero for a certain reflective endogenous latent variable are indicators of predictive relevance (Henseler et al., 2009, Hair et al., 2014, p. 178).

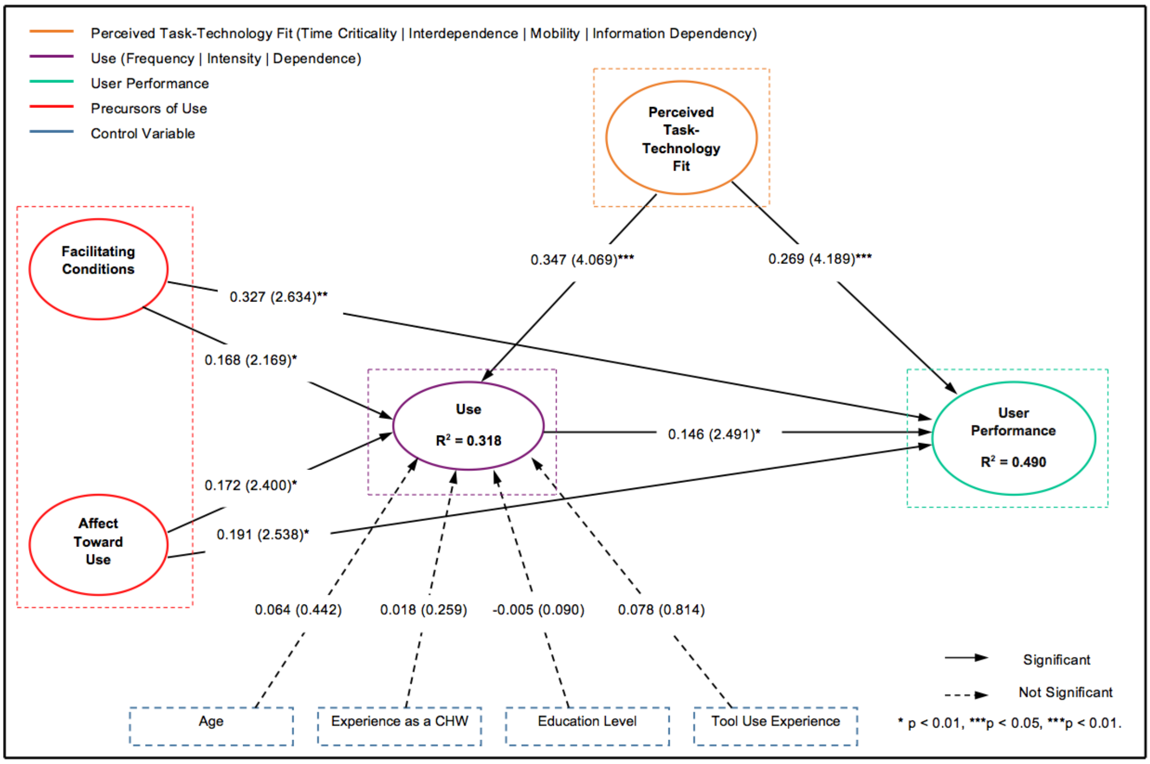

Figure 10.6. Path Model: Extended Technology-to-Performance Chain (TPC)

The path coefficients, *t* values, *p* values, significance levels, and confidence intervals, of the structural path model estimated to test the effects of (1) *facilitating conditions and affect toward use*, on use, (2) *perceived TTF* on *use* and *user performance*, and (3) *use* on *user performance*, are summarized in Table 10.3.

Table 10.3. Structural Path Model Results

Path	Path Coefficient	*t*	*p*	Significance	90% CI
Use → User Performance	0.176	2.491	0.01	**	[0.05, 0.24]
f^2 *Use → User Performance* = 0.025, q^2 *Use → User Performance* = 0.025					
Perceived TTF → Use	0.347	4.069	0.00	***	[0.21, 0.49]
Perceived TTF → User Performance	0.269	4.189	0.00	***	[0.16, 0.37]
f^2 *Perceived TTF → Use* = 0.299, q^2 *Perceived TTF → Use* = 0.385 f^2 *Perceived TTF → User Performance* = 0.096, q^2 *Perceived TTF → User Performance* = 0.068					
Facilitating Conditions → Use	0.168	2.169	0.03	**	[0.04, 0.30]
Affect Toward Use → Use	0.172	2.400	0.02	**	[0.05, 0.29]
f^2 *Facilitating Conditions → Use* = 0. 063, q^2 *Facilitating Conditions → Use* = 0.128 f^2 *Affect Toward Use → Use* = 0.072, q^2 *Affect Toward Use → Use* = 0.111					

NS = Not Significant, *p < 0.10, **p < 0.05, ***p < 0.01

Results in Table 10.3 indicate that *use* has a significant positive effect on *user performance* (path coefficient = 0.176, t = 2.491, p < 0.05). Thus the TPC is completed and ***Proposition 9 (P9)*** is supported. *Perceived TTF* has a significant positive effect on *use* (path coefficient = 0.347, t = 4.069, p < 0.01) and *user performance* (path coefficient = 0.269, t = 4.189, p < 0.01). Thus ***Proposition 10a (P10a)*** and ***Proposition 10b (P10b)*** are supported. *Facilitating conditions* has a significant positive effect on *use* (path coefficient = 0.168, t = 2.169, p < 0.05), and *affect toward use* has a significant positive effect on *use* (path coefficient = 0.172, t = 2.400, p < 0.05). Thus the TPC is extended and ***Propositions 11 (P11)*** and ***Proposition 12 (P12)*** are supported. *Perceived TTF* has stronger effects[78] on *use* (f^2 = 0.299, q^2 = 0.385) than *facilitating conditions* (f^2 = 0.063, q^2 = 0.128) and *affect toward use* (f^2 = 0.072, q^2 = 0.111), although *facilitating conditions* and *affect toward use* have small incremental effects on *use* over and above *perceived TTF*. *Perceived TTF* also has stronger effects on *user performance* (f^2 = 0.096, q^2 = 0.068) than *use* (f^2 = 0.025, q^2 = 0.025), although *use* has small incremental effects on *user performance* over and above *perceived TTF*. In prior works, demographic characteristics have been observed to influence technology use (Agarwal and Prasad, 1999; Venkatesh and Morris, 2000; Potagolu and Ekin, 2001; Piccoli, Ahmad and Ives, 2001). As such, the effects of *age*, *experience as a CHW*, *education level*, and *tool use experience,* on *use,* were controlled for in the estimation of the structural path model. However, these control variables were not found to have a significant effect on *use*.

10.6.2 Mediating Effects

Use was tested for mediating effects between (1) *perceived TTF and user performance*, and (2) *facilitating conditions and affect toward use* and *user performance*. The path coefficients, t values, p values, significance levels, and confidence intervals, of the structural path model estimated to test the effects of (1) *facilitating conditions and affect toward use* on *user performance* through *use,* and (2) *perceived TTF* on *user performance* through *use*, are summarized in Table 10.4.

[78] For f^2, values of 0.02, 0.15, and 0.35 are small, medium, and large effects, respectively (Cohen, 1988). These threshold values are also used to assess q^2 (Urbach and Ahlemann, 2010; Hair et al., 2014).

Table 10.4. Structural Path Model Results					
Direct Effects	Path Coefficient	*t*	*p*	Significance	90% CI
Perceived TTF → Use	0.347 ^{p1}	4.048	0.00	***	[0.21, 0.49]
Use → User Performance	0.146 ^{p2}	2.559	0.01	**	[0.05, 0.24]
Perceived TTF → User Performance	0.269 ^{p3}	4.193	0.00	***	[0.16, 0.38]
***Indirect Effect* = p^1 (0.347) x p^2 (0.146) = 0.051**					
Facilitating Conditions → Use	0.168 ^{p1}	2.117	0.04	**	[0.04, 0.30]
Use → User Performance	0.146 ^{p2}	2.559	0.01	**	[0.05, 0.24]
Facilitating Conditions → User Performance	0.327^{p3}	2.648	0.01	***	[0.12, 0.53]
***Indirect Effect* = p^1 (0.168) x p^2 (0.146) = 0.025**					
Affect Toward Use → Use	0.172 ^{p1}	2.420	0.02	**	[0.06, 0.29]
Use → User Performance	0.146 ^{p2}	2.559	0.01	**	[0.05, 0.24]
Affect Toward Use → User Performance	0.191^{p3}	2.224	0.03	**	[0.05, 0.33]
***Indirect Effect* = p^1 (0.172) x p^2 (0.146) = 0.025**					

NS = Not Significant, *p < 0.10, **p < 0.05, ***p < 0.01

The significance of the indirect effects was tested. In addition, the mediating strength of *use* was determined. Indirect effect sizes, bootstrapping standard errors, *t* values, and VAF values are summarized in Table 10.5.

Table 10.5. Indirect Effect and Mediation Strength Results									
Direct Effect	Size	Indirect Effect	Size	Total Effect	Standard Error	*t*	Significance	VAF	
								Value	**%**
Perceived TTF → User Performance	0.269	*Perceived TTF → Use → User Performance*	0.051	0.320	0.023	2.217	**	0.159	16%
Facilitating Conditions → User Performance	0.327	*Facilitating Conditions → Use → User Performance*	0.025	0.352	0.015	1.667	*	0.071	7%
Affect Toward Use → User Performance	0.191	*Affect Toward Use → Use → User Performance*	0.025	0.216	0.015	1.667	*	0.116	12%

NS = Not Significant. *p < 0.10, **p < 0.05, ***p < 0.01

Non-Mediation (VAF < 20%), Partial mediation (20% < = VAF < = 80%), Full mediation (VAF > 80%)

Total Effect = Direct Effect + Indirect Effect

Results in Table 10.5 indicate that the effect of *perceived TTF* on *user performance* through *use* (t = 2.217, p < 0.05) is significant. In addition, the effects of *facilitating conditions* (t = 1.667, p < 0.10) and *affect toward use* (t = 1.667, p < 0.10) on *user* *performance* through *use* are significant. In addition, *use* accounts for 16% (VAF = 0.159) of the *perceived TTF* effect on *user performance*, and 7% (VAF = 0.171) of the effect of *facilitating conditions* on *user* performance, and 12% (VAF = 0.116) of the effect of *affect toward use* on *user performance*. Since the VAF values obtained are smaller than 20%, almost no mediation occurs (Hair et al., 2014, p. 225). Thus *use* does not fully mediate the effects of *perceived TTF* on *user performance*, and the effects of *facilitating conditions* and *affect toward use* on *user performance*.

10.7 Discussion

10.7.1 The Link Between Use and User Performance

In this chapter, it was postulated that in the mHealth context technology use and user performance are significantly and positively associated. This is confirmed as findings indicate that mHealth tool use is significantly and positively associated with CHW performance. Notably, Trice and Treacy (1986) posited that technology if not used, cannot impact its users, and proposed a 'forward linkage' between the system, utilization and performance (p. 13). Similarly, Goodhue and Thompson (1995) posited that utilization positively impacts performance (p. 214), as did Goodhue, Littlefield, and Straub (1997, p. 461). Thus a 'forward linkage' is confirmed as higher technology use increases user task performance (Luarn and Huang, 2009, p. 235). Similarly, Chiasson, Kelley and Downey (2015) theorized and observed significant positive associations between use and performance, a linkage described as a feed-forward chain relationship (p. 169), and notably, in a prior study, Hsiao and Chen (2012) found that the use of mobile IS in a hospital setting enhances the effectiveness and efficiency of nurses in patient care performance.

10.7.2 The Link Between Task-Technology Fit (TTF) and Use and User Performance

It was also postulated that a perceived 'fit' between the task and the technology is significantly and positively associated with use and user performance. This is supported as findings indicate that the perceived 'fit' of the mHealth tool to the CHW task is significantly and positively associated with mHealth tool use and CHW performance. This is consistent with the observation that perceived TTF is a direct performance antecedent (Goodhue and Thompson, 1995), and that using technology with a high TTF would positively influence user performance because the tool or system used closely meets the task performed (Hsiao and Chen, 2012). This finding corroborates evidence in previous research that indicates that perceived TTF has positive impacts on both use and user performance outcomes (Luarn and Huang, 2009, p. 236, D'Ambra et al., 2013, p. 60). Technology use and its outcomes have been considered to be dependent on context (Tambe and Hitt, 2012) such that perceived TTF can be considered to have either negative or positive consequences for user performance. In some cases, users can choose to use a tool or system with low TTF more frequently to meet their needs. On the other hand, users can also choose to use a tool or system with high TTF more frequently because it sufficiently meets their needs (p. 53). Moreover, a perceived TTF may have diminished impacts on user performance levels if the user does not use the tool or system. Notably, the observed finding is not consistent with McGill, Klobas and Renzi's (2011) observation that perceived TTF does not influence utilization but was found to have a significant and positive effect on performance outcomes (p. 52). Similarly, McGill and Klobas (2009) found only positive perceived TTF performance effects (p. 503). It has been argued that in particular contexts, use is independent of a perceived 'fit' between the task and the technology (McGill et al., 2011, p. 53). It is notable that use is partly dependent on a perceived 'fit', and contributes to translating this perception into improved performance.

10.7.3 The Link Between Precursors of Use and Use

The identification of factors that affect the degree to which system users use technologies has been emphasized in previous research (Fuerst and Cheney, 1982; Thompson et al., 1991). In addition to perceived TTF, it was found that the precursors of facilitating conditions and affect toward use have significant impacts on use. Thompson, Higgins, and Howell (1994) posited that facilitating conditions are those factors that enable task performance (p. 170). This observation is consistent with Chang and Cheung's (2001) finding that facilitating conditions are positive and significant precursors of technology use (p. 9). Findings confirm these expectations such that CHWs are less likely to use systems when facilitating conditions e.g. training support and information resources, and positive affective evaluations of the technology, are absent. Selim (2007) observed that facilitating conditions such as accessibility, quality of infrastructure, and technical and financial support were significantly and positively associated with technology use (pp.

407-410). Moreover, Compeau and Higgins (1995) observed that the affective response of users towards a system impacts their usage behaviour (p. 196), and similarly, Compeau, Higgins, and Huff (1999) affirmed that affect toward use was a determinant of system usage (p. 153). Therefore in this study, mHealth tool use and the above precursors were expected to be significantly and positively associated. Findings thus confirm the importance of affect, and affirm that mHealth tool use is dependent on CHWs having a positive or enjoyable experience using the technology such that their frustration would inhibit its use.

10.7.4 The Technology-to-Performance Chain (TPC)

In addition to the postulated effects of perceived TTF on use and user performance, use was linked to user performance and a set of precursors, and as such, completed an extended TPC. In addition, use was positioned to mediate between these precursors and user performance. Trice and Treacy (1986) observed that in linking systems to performance impacts, utilization can be the conduit between 'backward and forward linkages' (p. 13). However, in the present study, mHealth tool use was not found to fully mediate the effects of affect toward use on CHW performance, thus contradicting LeBlanc and Kozar (1990) who observed that IT and performance are positively associated, but only through use as an intervening mechanism (p. 274). As such, depending on the context, IT that is enjoyable to use can directly impact user task performance. Based on results of TPC model (Figure 10.6) tests reported in this chapter, it was observed that perceived TTF and use have significant and positive impacts on user performance. Similarly, D'Ambra, Wilson and Akter (2013) found that a user-perceived TTF and utilization accounted for a significant amount of the variance in performance effects. It is noteworthy that perceived TTF was found to have a stronger impact on user performance than does use. This finding is consistent with previous studies in which it was found that perceived TTF has greater explanatory power than utilization in the prediction of performance impacts (Staples and Seddon, 2004, p.28; McGill and Klobas, 2009, p. 505). As such, the perceptions of CHWs of a 'fit' between their tasks and the mHealth tool is more important for their delivery of patient care than their levels of dependence on using it. In some previous studies however, utilization has been observed to be more strongly associated with perceived task performance than perceived TTF, such that the actual usage of a tool or system may not be contingent upon user perceptions of a ‘fit’ to task (Luarn and Huang, 2009, p. 236; D’Ambra et al., 2013, pp. 61-62). As such, in some user environments, enhancing use is believed to more directly impact task performance (p. 236). Moreover, it is possible that tool or system users can perceive that they are best assisted through the use of IT, which in turn enhances their task performance. Furthermore, it can be speculated that in some contexts, technology users accumulate sufficient experience using a particular tool or system and are thus familiar with its functionality such that a perceived ‘fit’ is not a determining factor for their task performance. It therefore appears that in prior works, findings indicative of ‘forward linkages’ from TTF and use, to performance, have been inconsistent. Perceived TTF is nevertheless found here to be essential for enhanced use and user performance. In addition, it is noteworthy that perceived TTF has a stronger impact on use than facilitating conditions and affect toward use. This result is consistent with Goodhue, Littlefield and Straub’s (1997) finding that perceived TTF was more highly correlated with utilization than the facilitating condition of accessibility (p. 461). Thus TTF as a theory for use has greater explanatory power than some of the other use theories. As McGill and Klobas (2009) observed, the role of TTF in directly impacting user performance is a core element of the TPC, as has been confirmed in previous research conducted in various contexts (Goodhue et al., 1997; Goodhue et al., 2000; D’Ambra and Wilson, 2004). In the present study, perceived TTF and use are core processes through which technology impacts user performance (Goodhue, 1992, p. 305; Goodhue and Thompson, 1995, pp. 217-220; Goodhue, 1997, p. 450; Goodhue, Littlefield and Straub, 1997, p. 455; D’Ambra and Wilson, 2004a, 2004b; Luarn and Huang, 2009, p. 229; D’Ambra, Wilson and Akter, 2013). Thus user performance can be considered a function of both perceived TTF and use (Staples and Seddon, 2004; Luarn and Huang, 2004), and use a function of both perceived TTF and precursors of use (Goodhue et al., 1997). Within the extended TPC model tested in the context of the present study, TTF is a significant predictor of use and user performance when CHWs perceive a ‘fit’ between their tasks and characteristics of the mHealth tool, in addition to their dependence on using it, and positively and affectively evaluate the technology. Therefore considered retrospectively, the empirical evidence adduced in this chapter serves to affirm, clarify, and extend the relationships between technology, TTF, use and performance through ‘forward and backward linkages’ (Trice and Treacy, 1986; Goodhue, 1995; Goodhue and Thompson, 1995; Staples and Seddon, 2004; Luarn and Huang, 2009; Chiasson et al., 2015). Therefore findings lend support to Goodhue and Thompson's (1995) proposed integration of use and fit models into a TPC.

10.7.5 Implications for Research

There are seven implications for research, arising from this chapter's test of the extended complete TPC model.

First, use comprises the dimensions of 'frequency', 'duration', and 'dependence', together forming a composite construct, which is useful in that it can be empirically examined for its effects on user performance. The inclusion of frequency and duration dimensions to supplement use as dependence, extends the TPC, thereby representing an enriched perspective of the use construct beyond perceptions of user dependence on the tool.

Second, the evaluation of multiple use dimensions meaningfully extends TTF theory. In addition, by linking use to user performance, the 'forward linkage' of the TPC is completed (Trice and Treacy, 1986). It is apparent that this linkage ought to be incorporated as an essential component of causal chains. This gives more impetus to LeBlanc and Kozar's (1990) observation that to fully grasp the relationship between technology and performance, utilization can and must play a significant role as a predictor (p. 263).

Third, 'facilitating conditions' and 'affect toward use' were examined as precursors of technology use in the present study. By linking these precursors to use, a 'backward linkage' of the TPC extended the model (Trice and Treacy, 1986). This relationship is especially useful for researchers who endeavour to understand and explain the incremental effects of use precursors in a TPC.

Fourth, observed findings can greatly benefit researchers testing mHealth tool use precursors in multiple contexts. Subsequently, the findings reported in this study can enhance pre-existing, limited research on determinants of use. It would, therefore, be prudent for theorists developing and testing TPCs to re-assess the linkages between use and its determinants.

Fifth, it is important for researchers to simultaneously consider the determinants of use and its impacts on user performance. This represents a more balanced and precise approach for researchers who endeavour to exhaustively investigate the role of technology use behaviour in linking task and tool components and other user perceptions to user performance.

Sixth, it is important to recognize that in testing the use construct as an intervening mechanism, simultaneous 'backward and forward linkages' must be anticipated, and not necessarily one or the other. This enriches the currently existing research on the determinants and consequences of technology use. Moreover, this approach signifies a multi-functional perspective of technology use. Thus researchers must recognize and validate that in addition to TTF, precursors are alternative use determinants that could substantively impact user performance.

Seventh, following this study, it must be appreciated that TPC components together form a causal chain that must be systematically and sequentially evaluated. Consequently, researchers can use the TPC as an analytical framework useful for evaluating technology impacts in a particular context. They could also empirically assess the robustness of linkages in the causal chain to identify those components that need strengthening. For example, in this study, TTF was tested as perceived TTF but further work could be replicated to consider TTF modelled as Covariation within an extended TPC model for example. Alternative conceptualizations of use such as 'deep structure use and 'presence of use' could also be considered.

10.7.6 Implications for Practice

There are six implications for practice, arising from this chapter's test of the extended complete TPC model.

First, mHealth tool designers should consider the link between use and CHW performance. In doing so, they must prioritize those factors that are instrumental to technology use in a particular context. To derive performance benefits, technology must be used and for use to occur, tool user preferences must be anticipated along with facilitating mechanisms e.g. decision support, technical support, logistical support, training support, access to supplies, information resources, access to feedback mechanisms, and adequate mobile coverage.

Second, as demonstrated in this study, an evidence-based understanding of the relationship between use and user performance represents invaluable feedback for technology designers, instrumental to their design of enhanced, user-responsive mHealth tools for CHW tasks. In addition, findings of this study represent empirical support for the importance of forward linkages as a critical component of enhanced patient care delivery.

Third, mHealth tool designers must recognize the importance of the CHW as the end-user. CHW input must, therefore, be incorporated to better anticipate user perceptions, and identify those factors that directly influence mHealth tool use. Designers must also focus on translating mHealth tool use into CHW performance through an enhanced user 'task-fit' experience. Findings are thus useful for those who may wish to design superior mHealth technologies. This can be achieved by identifying what factors both influence and affect tool use behaviour in the CHW context. As the intended users of the technology, it is important that CHWs be involved as participants in the design process, so as to ensure that the mHealth tool they are equipped with 'fits' their task needs, while also satisfying standard best practices for the effective delivery of patient care.

Fourth, designers must design more user-friendly mHealth tools to create a CHW dependence on use. In addition, they could use a set of metrics with which to customize CHW user preferences. This is to ensure that the tools are more enjoyable and less frustrating to use, thereby enhancing the affective response of users to the tool used. A more scientific, data-driven approach to mHealth tool design must, therefore, be adopted to guide design.

Taken together, designers could use the TPC as a multi-purpose, diagnostic evaluative framework for (1) re-designing mHealth tools and CHW support functions to enhance user perceptions of a 'fit' of the technology to task, (2) prioritizing functions that can enhance CHW performance, and (3) involving CHWs to enhance mHealth tool use impacts on their user experience.

It is clear that the findings reported constitute important practical implications for mHealth projects in which implementers wish to support CHW-assisted patient care delivery systems. In doing so, well-designed mHealth tools sensistive to the task requirements of CHW users would be used to enhance their performance and could complement or even replace existing technologies.

10.8 Chapter Conclusion

The purpose of this chapter was to evaluate the determinants of technology use and its impacts on user performance. First, use was examined for its effect on user performance. Use was found to have a positive influence as a determinant of user performance besides TTF. Second TTF was examined for its effects on use and user performance. TTF was found to have a positive influence on use and user performance. Third, the precursors of facilitating conditions and affect toward use were examined for their effects on use. Facilitating conditions and affect toward use were found to have a positive influence as determinants of use besides TTF. Fourth, use was examined for mediating effects between TTF and user performance, and the precursors of facilitating conditions and affect toward use, and user performance. Use was not found to mediate between TTF and user performance, and facilitating conditions and affect toward use and user performance. Overall, in this chapter, a completed and extended TPC model has been empirically substantiated.

Results of tests of determinants of use and its impacts on user performance are summarized in Table 10.6.

Table 10.6. Findings

Proposition		Finding
P9	The use of mHealth tools by CHWs will positively influence user performance.	Supported
P10a	The perceived ‘Fit’ between CHW tasks and mHealth tools will positively influence use.	Supported
P10b	The perceived ‘Fit’ between CHW tasks and mHealth tools will positively influence user performance.	Supported
P11	Affect toward use will positively influence mHealth tool use.	Supported
P12	Facilitating conditions will positively influence mHealth tool use.	Supported

11 Conclusion

11.1 Introduction

The purpose of this study was to examine the implications of mHealth tools for the performance of CHWs in the Kenyan context and to evaluate how supporting technology characteristics ‘fit’ with CHW task characteristics to influence the use of mHealth tools. Several knowledge gaps in previous mHealth research, and emergent research problems were identified. To address these research problems, seven research questions were formulated[79]. To answer these research questions, nine study objectives were specified[80]. To address these study objectives, a conceptual model was developed[81] to link mHealth technology to CHW performance. The purpose of this chapter is to conclude this study by (1) Summarizing the study, (2) Discussing the research limitations of the study, (3) Highlighting contributions of this study to theory and practice, and (3) Discussing the implications of the study for future research. Chapters 2 to 10 of this thesis are summarized in Section 11.2.

11.2 Summary of the Study

In Chapter 2, literature on mHealth and CHW performance was reviewed, and shortcomings were identified. The context of this study was the use of mHealth tools among CHWs in Kenya. In Chapter 3, a quasi-experimental post-test study of non-equivalent groups (Harris et al., 2006) was conducted to compare the performance of CHWs using mHealth tools to those using traditional paper-based systems, in the Kenyan context. The intervention, mHealth tool use (X), was observed in one group, and not the other, a control group comprising traditional paper-based systems users. It was found that mHealth tool users outperform their counterparts using paper-based systems as they spend less time completing their monitoring, prevention, and referral reports weekly, and report higher percentages of both timeous and complete monthly cases. Although no significant differences were found along the demographic indicators of gender, education level, and use experience, it was observed that they had significant effects on CHW

[79] Please refer Section 1.3 of Chapter 1 for a description of the Research Questions formulated for this study.
[80] Please refer Section 1.4 of Chapter 1 for a description of the Study Objectives specified for this study.
[81] The development of this conceptual model is detailed in Chapter 5, and the conceptual model is presented in Figure 5.12 of Chapter 5.

reporting performance between the two user groups. Moreover, while in some instances paper-based system users may initially perform better, mHealth tool users gradually accumulate sufficient experience catching up to, and eventually surpassing their more conventional counterparts. In addition, mHealth tool users were found to be more positive about their performance compared to those using traditional paper-based systems. Study Objectives 1 and 2 were addressed and thus answers to Research Questions 1 and 2 were provided. Having established the relative advantage of mHealth tools for CHW performance, the theory of Task-Technology Fit (TTF) was then drawn on to better understand the within-group variation in tool use and user performance, among mHealth tool users, who were the primary units of analysis in this study.

In Chapter 4, the concept of TTF was identified as the theoretical underpinning of this study. In Chapter 5, a Technology-to-Performance Chain (TPC) underpinned by TTF theory was developed to link CHW task and mHealth technology characteristics to mHealth tool use and CHW performance. Previous research in which TPC models have been developed and empirically tested were built upon. In past studies on TPC concepts, constructs including 'system characteristics', 'task-system fit', 'expected consequences of use', 'affect toward using', and 'performance impacts' (Goodhue and Thompson, 1995; Goodhue, 1997; Goodhue et al., 1997; Staples and Seddon, 2004) have been linked. However, as Staples and Seddon (2004) noted, while TPCs have been proven useful for testing theory, explanation, and prediction, the linkages between their constructs have not been exhaustively evaluated especially in prior TTF-influenced research (p. 18).

This study was therefore positioned to constitute a unique contribution through the development of a TPC to link the constructs of Task-Technology-Fit (TTF) (A), use (B), user performance (C), and a set of precursors (D). As reproduced in Figure 11.1, this TPC was a complete, extended conceptual model developed for, and comprehensively tested in, the context of mHealth tool use and CHW performance in Kenya. First, TTF was linked to use and user performance (Links 1.1 and 1.2), from multiple adopted 'fit' perspectives (Venkatraman, 1989). Second, use was linked to user performance (Link 2). Third, a set of precursors of use was linked to use (Link 3).

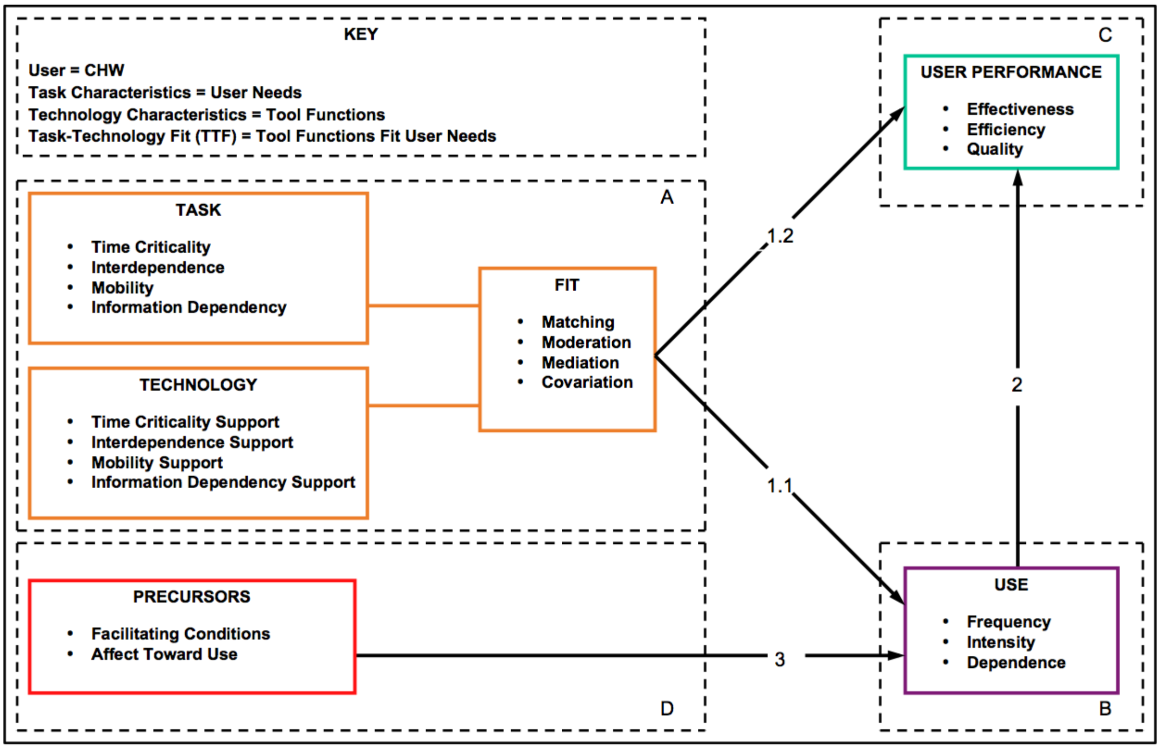

Figure 11.1. Tested Completed and Extended Technology-to-Performance Chain (TPC)

TTF is the core process in the TPC. TTF is a multi-faceted construct, which has often been described as the extent to which a system assists users in performing their tasks (Goodhue, 1992), or the 'fit' of system or tool support functions to task requirements (Dishaw, 1994; Goodhue and Thompson, 1995). As observed, in some prior works, the user typically evaluates the 'fit' of the tool used to the task performed. Elsewhere, 'fit' is computed as a bivariate term combining task needs and tool support functions (Dishaw, 1994). TTF has been linked to both tool utilization and user performance outcomes (Goodhue, 1992; Dishaw, 1994; Goodhue and Thompson, 1995). Four 'fit' perspectives were adopted from Venkatraman (1989) and used to operationalize TTF and its effects on use and user performance. As such, by conducting the study, research on the nature and impacts of 'fit' was meaningfully extended. TTF was examined not only as a user-evaluated construct (Chapter 8), but also as a configured, computed, by-product of its underlying task and technology characteristics (Chapters 6 and 7). Moreover, TTF was examined for non-linear effects on use and user performance. Furthermore, for the first time, TTF was examined as an internally consistent, observable pattern of co-aligned, inter-related characteristics, tested for its consequent effects on use and user performance (Chapter 9). To conceptualize TTF for this study, its underlying task and technology characteristics were defined and operationalized, as described in Chapters 3 and 4. The task characteristics of CHW work were defined in terms of time criticality, interdependence, mobility, and information dependency dimensions. The technology characteristics of the mHealth tool were defined as support functions for time criticality, interdependence, mobility, and information dependency. The adoption of multiple 'fit' perspectives was important to ensure that useful insights into the complex, dynamic interplay between task and technology characteristics were comprehensively analysed, offering a more in-depth explanation of TTF. A discussion of the results of testing of the adopted 'fit' perspectives is described as follows:

First, in Chapter 6, the perspective of Fit as Matching (Venkatraman, 1989, p. 430) was adopted and used to operationalize TTF as the corresponding pairs of user needs and tool functions. Four paired matches were examined for their effects on mHealth tool use and CHW performance. Tests of TTF as Matching showed that time criticality fit was important for user performance, but that interdependence fit was not important. In addition, mobility fit could be negative for use and user performance because unlike CHWs with low task mobility, the dependence on the mHealth tool and patient care effectiveness, efficiency, and quality, of those with relatively high task mobility is not contingent upon the characteristics of the technology used.

Second, in Chapter 7, the perspective of Fit as Moderation (Venkatraman, 1989, p. 424) was adopted and used to operationalize TTF as the cross-product interactions of user needs and tool functions. Sixteen combinations signifying interacting fit pairs[82] were examined for their effects on use and user performance. Tests of TTF as Moderation showed that a mobility-interdependence fit was important for both use and user performance, and that a mobility-information dependency fit was important for user performance. Similarly, an information dependency-time criticality fit was important for user performance. It was also found that TTF as interaction had significant non-linear effects on mHealth tool use and CHW performance.

In addition, a perfect fit (congruence) between composite CHW task and mHealth technology components was observe to influence the highest levels of tool use. However, a misfit (incongruence) between the CHW task and mHealth technology was found to

[82] Please refer discussion in Section 7.4.2 and Figure 7.3 in Chapter 7.

influence lower levels of tool use. Likewise, the perfect fit (congruence) between the CHW task and the mHealth technology was found to influence the highest levels of user performance, whereas a misfit (incongruence) between the CHW task and mHealth technology was found to influence much lower levels of user performance. Moreover, it was found that an over-fit (excessive functional support) of the mHealth technology to the CHW task leads to a decline in levels of tool use. Furthermore, results also indicated that an under-fit (insufficient functional support) of the mHealth tool to the CHW task leads to a decline in levels of user performance.

Third, in Chapter 8, the perspective of Fit as Mediation (Venkatraman, 1989, p. 428) was adopted and used to operationalize TTF as an intervening construct between user needs and tool functions, and use and user performance. Four identified user-perceived fit dimensions were evaluated. It was found that user-perceived fit fully mediates the effects of the mobility of CHW tasks on mHealth tool use, but partially mediates the effects of mHealth tool support for CHW task time criticality, interdependence, and information dependency, on the use of the mHealth tool. Moreover, user-perceived fit partially mediates the effects of time criticality of CHW tasks on user performance. However, this perceptual fit was not found to mediate the effects of CHW task interdependence, mobility, and information dependency, on user performance. Furthermore, user-perceived fit fully mediates the effects of mHealth tool support for time criticality on user performance, but partially mediates the effects of mHealth tool support for interdependence and information dependency, on user performance. In addition, a TTF combination of the four dimensions of user-perceived fit, as a set of simultaneous intervening mechanisms, was found to be a significant predictor of mHealth tool use and CHW performance.

Fourth, in Chapter 9, the perspective of Fit as Covariation (Venkatraman, 1989, p. 435) was adopted and used to operationalize a holistic TTF system observed as a discernible pattern of co-aligned and internally consistent user needs and tool functions, examined for its effects on use and user performance. It was found that the inter-relatedness of CHW task time criticality, interdependence, mobility, and information dependency, and co-aligned mHealth tool time criticality support, interdependence support, mobility support, and information dependency support, was established as these co-aligned factors were found to be significant first-order dimensions of a second-order fit. This second-order fit was representative of their co-alignment and internal consistency. Subsequently, this 'fit' as co-alignment and internal consistency, was found to be a significant predictor of mHealth tool use and CHW performance, thereby providing an additional, more nuanced perspective of TTF, not conceptualized in prior works. In essence, this is neither a computed nor user-perceived TTF as has been expressed in various forms in previous studies, but is instead a holistically configured combination of user needs and tool functions. Thus a significant alternative 'fit' configuration that can be observed to have impacts on use and user performance is represented.

For additional insight, the predictive significance of each of the four TTF-modelled[83] 'fit' perspectives is summarized in Table 11.1.

Table 11.1. Task-Technology Fit (TTF) Model Comparison

Criterion	Use				User Performance			
Model	Matching	Moderation	Mediation	Covariation	Matching	Moderation	Mediation	Covariation
R^2_{adj}	0.264	0.332	0.244	0.157	0.432	0.561	0.334	0.251
Q^2_{adj}	0.129	0.107	0.093	0.058	0.245	0.301	0.172	0.134

As indicated in Table 11.1, the predictive accuracy (R^2) and relevance (Q^2) for use and user performance, of the TTF models tested for their combined effects, were estimated. To account for the dimensionalities of each modelled 'fit', Adjusted R^2 (R^2_{adj}) and Q^2 (Q^2_{adj}) values were calculated[84]. The adjusted R^2 (R^2_{adj}) values for use and user performance are significant across the various models. Similarly, across the models, all the values of the cross-validated redundancy measure Q^2 (Q^2_{adj}) are significant. Overall, the R^2_{adj} and Q^2_{adj} of Moderation for use (R^2_{adj} = 0.332, Q^2_{adj} = 0.107) and user performance (R^2_{adj} = 0.561, Q^2_{adj} = 0.301), and Matching for use (R^2_{adj} = 0.264, Q^2_{adj} = 0.129) and user performance (R^2_{adj} = 0.432, Q^2_{adj} = 0.245), are the highest and most significant across all the models. In addition, the R^2_{adj} and Q^2_{adj} of Mediation for use

[83] Note: In Chapters 6 to 8, and in addition to TTF examined for covariation effects in Chapter 9, TTF was also modelled and tested for simultaneous effects on use and user performance, as detailed in Section 6.5.5 of Chapter 6, Section 7.5.5 of Chapter 7, Section 8.5.5 of Chapter 8, respectively. In these sections, the overall predictive significance of the TTF models tested was determined.

[84] The following formula (Hair et al., 2014) was used to calculate R^2_{adj} values, where n is the sample size and k is the number of exogenous latent variables (predictors) in the estimated structural path models (p. 176): The same formula was used to calculate Q^2_{adj} values, by substituting R for Q in the formula (Sarstedt et al., 2013).

$$R^2_{adj} = 1 - (1 - R^2) \cdot \frac{n - 1}{n - k - 1}$$

(R^2_{adj} = 0.244, Q^2_{adj} = 0.093) and user performance (R^2_{adj} = 0.334, Q^2_{adj} = 0.172) is lower, and the R^2_{adj} and Q^2_{adj} of the TTF as Covariation model for use (R^2_{adj} = 0.157, Q^2_{adj} = 0.058) and user performance (R^2_{adj} = 0.251, Q^2_{adj} = 0.134) is the lowest, and least significant of the models.

Technology (Tool Function)

Task (User Need)

	Time Criticality Support	Interdependence Support	Mobility Support	Information Dependency Support
Time Criticality	1 FIT	2 FIT	3 FIT	4 FIT
Interdependence	5 FIT	6 FIT	7 FIT	8 FIT
Mobility	9 FIT	10 FIT	11 FIT	12 FIT
Information Dependency	13 FIT	14 FIT	15 FIT	16 FIT

Figure 11.2. Task-Technology Fit (TTF) Matrix: The Integration of Matching and Moderation Interactions

As illustrated (Figure 11.2), interaction encapsulates both the Moderation and Matching 'fit' perspectives. This configuration exposes an apparent fundamental difference between the cellular[85] matching and non-matching of 'fit' interactions. The phenomenon of TTF can be represented as a paradigm that is either tool user-perceived, or computed as a bi-variate construct. As such, TTF is as much a cognitive process, as it is a calculated or computed by-product (Dishaw, 1994). TTF is neither restricted to Matching nor Moderation (interaction). Therefore it can be postulated that TTF can at once be captured as matching, moderation (interaction), and user-evaluation, thus lending credence to its potential versatility. There is, however, an alternative approach that has been seldom tested in past studies. 'Fit' can also be considered as a system of holistic configuration examined for covariation effects, although it appears that this perspective provides less of an explanation of its effects on use and user performance, than the alternative manifestations of TTF examined in this study.

In its totality, a 'fit' between task and technology characteristics can be evaluated through multiple perspectives adopted to understand TTF as a distinctive, multi-faceted, multi-dimensional, construct. As such, the TTF construct can be (1) matching, (2) cross-product

[85] Distinctive TTF matrices configured for Matching and Moderation (interaction) 'fit' perspectives are described and depicted in Figures 6.1 and 6.3 of Chapter 6, and Figure 7.3 of Chapter 7, respectively.

interaction, (3) user-evaluation, and (4) observed as a pattern of inter-related components. The complex and nuanced disposition of the 'fit' concept was thus aptly demonstrated in this study. Using this concept, the effects of TTF on use and user performance were established. Study Objectives 3 to 5 were addressed and therefore answers to Research Questions 3 and 4 were provided.

In Chapter 10, use was examined for its effects on user performance, and the two precursors 'facilitating conditions' and 'affect toward use', were examined for their effects on use. A perceptual TTF construct was also examined for its effects on use and user performance. It was found that mHealth tool use had a positive effect on CHW performance, thereby completing the TPC. It was also found that 'facilitating conditions' and 'affect toward use' had positive effects on mHealth tool use, thereby extending the TPC. Furthermore, perceived TTF was found to have positive effects on mHealth tool use and CHW performance. Of note, perceived TTF was found to be a stronger predictor of use than the tested precursors of use, and a stronger predictor of user performance than use. This is an affirmation of perceived TTF as the core process[86] through which use and user performance effects are observed. Study Objectives 6 to 9 were addressed and thus answers to Research Questions 5 to 7 were provided. By addressing Study Objectives 3 to 9 to answer Research Questions 3 to 7, a completed and extended TPC was effectively and fully tested, and empirically substantiated. Next, the theoretical and methodological limitations of this study are identified in Section 11.3.

11.3 Limitations of the Study

In this study, the impact of mHealth tools on CHW performance was empirically examined. To achieve this, a quasi-experimental post-test research design was used in Chapter 3, and an explanatory, predictive, research design was used in Chapters 6 to 10. However, a number of theoretical and methodological limitations of the study are noted.

First, this study was designed and implemented as field research. As such, there are limitations that are inherent in any field study. For instance, in this study, the researcher

[86] The various mechanisms or processes through which technology can be linked to performance are described in detail in Section 4.7 of Chapter 4.

had limited control over the design of mHealth technologies that were implemented and currently in use, and standard mHealth project protocols that were already instituted.

Second, a cross-sectional survey strategy (Saunders et al., 2010, p. 190) was used for this study. Structured questionnaire instruments (Orlikowski and Baroudi, 1991) were developed and used to collect data from respondent CHWs operating in Kenya. A cross-sectional survey design is useful for collecting respondent data at a single point in time. However, the long-term impact of TTF on use and user performance over time is not, therefore, observable. Moreover, the cross-sectional survey strategy used in this study imposes a limitation on the inference of causal relationships between model constructs other than those associations that are theoretically underpinned.

Third, owing to the use of a survey design consistent with empirical positivism, the nature of this study dictated that although technology user behaviour can be predictively modelled, it was not possible to qualitatively explore more extensive societal implications of mHealth tool use among CHWs in low-resource settings. The focus of this study on quantitative analysis prevented more qualitative insights into relationships between 'TTF', 'use', 'user performance', and 'precursors of use'.

The quasi-experimental post-test study detailed in Chapter 3 had the following limitations. First, the observed intervention, mHealth tool use, was not introduced prior to conducting the quasi-experiment. Consequently, CHWs were not randomly assigned to the intervention or control groups. This lack of random assignment has been cited as a weakness of quasi-experimental study designs (Harris et al., 2006, p. 17). Moreover, since the observed intervention was already underway at the time of the study, it was not possible to establish baseline equivalence.

Second, in any given empirical study, it is difficult to measure or control for all possible important confounding variables, particularly those that are unmeasured. This lack of sufficient control for confounds stems from a lack of randomization that is inherent in quasi-experiments, as conducted in this study. A higher number of potential confounding variables that are unmeasured or immeasurable cannot be controlled for in non-randomized quasi-experimental studies, but are part of the randomization processes inherent in randomized controlled trials (Harris et al., 2006, p. 18), that are more typical in clinical health informatics research. However, it must be recognized that despite observed limitations in controlling for possible confounding effects, the quasi-experimental design used in this study allowed for the opportunity to observe large numbers of technology users in their actual real-world setting.

The explanatory, predictive study detailed in Chapters 6 to 10 had the following limitations.

First, self-reported seven-point Likert scale measurement items (Bhattacherjee, 2012) were used to measure the constructs Task, Technology, Fit, Use, User Performance, and Precursors of Use. The employment of self-administered instrument indicators can be a possible source of respondent bias (p. 39). In this regard, more objective measurement indicators can be considered by future researchers to supplement more perceptual, self-administered scale item measures.

Second, although there was a high response rate, there were some unusable responses that needed to be omitted. There is no a priori expectation that the omitted respondent would differ from the usable responses. However, any differences that might exist would limit the external validity or generalizability of the findings of this study to the full population of CHWs.

Third, the precursors 'facilitating conditions' and 'affect toward use' were tested for their effects on use. The selection of these precursors in this study was in no small part motivated by deliberate theoretical considerations for the intended purpose of extending the developed TPC. It must, however, be acknowledged that there could be other precursors of mHealth tool use by CHWs in low-resource developing world contexts. Together with perceived TTF, the precursors evaluated in this study explained 31.8% of the variance in use, leaving nearly 70% of the variance unexplained. The impact of alternative determinants of technology use in such contexts, must, therefore, be investigated further.

In summation, the degree of influence of limitations identified in this study cannot be quantified. However, it is important that findings reported in this study should be recognized as substantive empirical evidence indicative of specific outcomes, rather than as conclusive, thus warranting their careful interpretation and subsequent application. The limitations highlighted, are, however, far outweighed by the contributions of this study to research and practice. These contributions are identified and discussed in Section 11.4.

11.4 Contributions of the Study

There were important contributions of the present study to theory, methodology, practice, and context.

11.4.1 Contributions to Theory

First, in Chapter 5, four dimensions of task and technology characteristics relevant to the CHW mHealth context, namely ‘time criticality’, ‘interdependence’, ‘mobility’, and ‘information dependency’, were conceptualized. The ‘task’ component specified in this study has characteristics that reflect CHW needs, while the ‘technology’ component has characteristics that reflect mHealth tool functions. Consequently, in this study, a ‘fit’ between these CHW user needs and mHealth tool functions was specified. These task and technology characteristics can be used in future work as a basis for examining mobile health work and how mobile technology tools support work tasks.

Second, in Chapter 6, the perspective of Fit as Matching (Venkatraman, 1989, p. 430) was conceptualized and examined as four matched pairs of task and technology characteristics tested for their effects on use and user performance. Specifically, these matched-fit pairs were tested for their independent and combined effects on use and user performance. To the researcher’s knowledge, this study is the first to adopt this approach to conceptualizing and testing TTF as Matching.

Third, in Chapter 7, the perspective of Fit as Moderation (Venkatraman, 1989, p. 424) was conceptualized and examined as sixteen cross-product interactions between pairs of task and technology characteristics, tested for their effects on use and user performance. These cross-product interaction ‘fit’ pairs were tested for their effects on use and user performance both independently, and in combination. This interaction TTF perspective was mechanically enhanced through the non-linear analysis of response surfaces (Edwards, 2002; Yang et al., 2013). These formulations of ‘fit’ extend and enrich TTF testing in IS research.

Fourth, in Chapters 6 and 7, TTF matrices were devised and used to configure the numerous possible matching or cross-product interaction 'fit' combinations between user needs and tool functions. Other IS researchers can use these matrices to visualize interactive TTF combinations and guide them in the computation of 'fit'. The use of TTF matrices to assess these distinct configurations of 'fit' as an interaction term (Venkatraman, 1989), therefore, represents a more novel and innovative schematic representation of the construct.

Fifth, in Chapter 8, the perspective of Fit as Moderation (Venkatraman, 1989, p. 428) was examined as four dimensions of perceptual, user-evaluated, intervening mechanisms, between determinant task and technology characteristics, and consequent use and user performance outcomes. These intervening and user-evaluated 'fit' constructs were tested for their mediating effects, both in independent models, and as simultaneous multiple mediators in a combined effects model. Of note, it appears that in prior works, user-evaluated TTF has not been explicitly specified as both a user-perception and an intervening mechanism in a single study. As such, this signifies a more complete approach to testing perceived TTF in IS research, while at the same time enriching the Mediation 'fit' perspective.

Sixth, in Chapter 9, the perspective of Fit as Covariation (Venkatraman, 1989, p. 435) was examined as a pattern of observed co-alignment among four inter-related task and technology characteristics, tested for their internal consistency, and subsequent effects on use and user performance. To the researcher's knowledge, this is the first time in TTF research, where 'fit' is evaluated from the Covariation perspective. Moreover, in evaluating Covariation, the concept of 'fit' is represented both as co-alignment and internal consistency. The task and technology characteristics observed were reflective first-order indicators of a 'fit', which was modelled as a reflective second-order construct. In addition, for the first time in TTF research, the co-alignment and internal consistency of 'fit' variables and subsequent covariation effects, were differentiated, therefore clarifying a common misconception that these manifestations are necessarily interchangeable, and demonstrating that they are, in fact, distinguishable.

Seventh, the adoption and comparison of various conceptual models, and the contrasting of findings following tests of TTF from multiple 'fit' perspectives, itself constitutes a conceptual contribution over prior works in which only one TTF model has been considered and examined. There are unique insights that emerge from adapting four distinct perspectives of ‘fit’. Specifically, the matched-pairing of corresponding user needs and tool functions could have both positive and negative impacts on mHealth tool use and CHW performance. Moreover, cross-product paired-interactions between user needs and tool functions do not necessarily have to match and could similarly have positive and negative impacts on mHealth tool use and CHW performance. Furthermore, ‘fit’ as a user perception can partially or fully mediate relationships between mHealth technology and CHW task characteristics, and mHealth tool use and CHW performance. As a full mediator, it is possible for a perceived fit to effectively suppress any negative effects of CHW task needs on use and user performance levels. Last but not least, fit as a holistically configured representation as a higher-order factor observed in terms of a pattern of co-aligned lower-order user needs and tool functions, can also have positive impacts on use and user performance.

Eighth, in Chapter 10, a complete, extended TPC was tested through a ‘forward linkage’ between use and user performance, and a ‘backward linkage’ between a set of precursors and use. In addition, a perceived TTF construct was tested for its effects on use and user performance. In doing so, perceived TTF and precursors of use were tested as determinants of use, and TTF and use were tested as determinants of user performance. Of note, use was positioned as an intervening mechanism firstly between perceived TTF as a determinant, and consequent user performance, and secondly between a set of use precursors as determinants, and consequent user performance. However, although in this study use was not found to mediate between these linkages, its positioning as mediating in the TPC represents a meaningful first attempt thereby progressing TTF and TPC research. As such, the use construct can at once be examined as a determinant of user performance, a consequence of both perceived TTF and a set of precursors, and a potential mediator, thus setting a precedent for a re-assessment of its importance as a multi-purpose TPC construct. In essence, the TPC theorized in Chapter 4 and developed in Chapter 5 is further validated. As such, all its postulated causal mechanisms are substantiated to affirm the importance of the technology-to-performance chain as a relevant theoretical framework from which to understand how technology supports task characteristics to influence user performance outcomes. As evidenced in Chapter 10, perceived TTF was found to be a stronger predictor of use than the precursors ‘facilitating conditions' and 'affect toward use', which were also observed to be significant determinants of use. In addition, perceived TTF was found to be a stronger predictor of user performance than was use, which was itself found to be a significant determinant of user performance. This represents insights into this core TPC process, further validating that as asserted in Chapter 4[87], TTF is a primary determinant of use and user performance. However, it is abundantly clear that to supplement TTF for the extent of the TPC to be fully appreciated, use must impact user performance, and in turn be impacted by precursors. Lastly, to incorporate and examine these precursors of use, it was aptly demonstrated that system use theories such as Expectancy Value Theory (Triandis, 1979; Bagozzi, 1982; Azjen, 1985, 1991) can be effective supplementary theories, therefore meaningfully extending the theory of TTF (Vessey, 1991; Vessey and Galleta, 1991; Goodhue, 1992; Dishaw, 1994; Vessey, 1994; Goodhue, 1994; Goodhue and Thompson, 1995) and strengthening the TPC.

11.4.2 Contributions to Methodology

First, in Chapter 3, a quasi-experimental post-test design with non-equivalent groups (Harris et al., 2006; Leedy and Ormrod, 2013, Creswell, 2014) was used to evaluate CHW performance groups using mHealth tools compared to traditional paper-based systems. Such a study design is rare in IS literature, but as evidenced in this study, has been proven to be uniquely useful for understanding the relative advantages of mHealth tools on CHW performance.

Second, in Chapters 6 and 7, continuous moderator effects were modelled using product indicators (Henseler and Fassott, 2010). In addition, 'fit' interactions relative to use and user performance were graphically plotted to observe the interplay between user need and functional support levels. This signifies useful technical insights into moderator effect analyses with the possibility of interactive TTF visualization.

Third, in Chapter 7, Polynomial Regression with Response Surface Methodology (RSM) (Edwards, 1993, 2002; Shanock et al., 2010; Yang et al., 2013) was used to evaluate TTF for its non-linear effects on use and user performance. For the first time in TTF research

[87] Please refer Chapter 4 for a detailed discussion of the theory of TTF, the TTF construct, and the TTF model.

situated in the health informatics research space, this sophisticated three-dimensional (3D) technique is applied, as it allows for enhanced predictive precision.

Fourth, in Chapters 8 and 10, mediator analyses with bootstrapping procedures (Preacher and Hayes, 2004; Hair et al., 2014) were used to test indirect effects on user performance. Specifically, the effects of user needs and tool functions on use through perceived fit were tested. Similarly, their effects on user performance through perceived fit were tested. The effects of precursors on user performance through use were also tested. These mediator analyses represent the significance of testing multiple mediating relationships between a set of determinants and consequent variables, in TTF research, as demonstrated through this study.

Fifth, in Chapter 9, TTF was modelled as a reflective first-order, reflective second-order construct. As such, the first order factors were reflective indicators of the second-order construct. For the first time in IS and by extension, TTF research, confirmatory second-order factor analyses were used to examine the concept of 'fit' and its effects on consequent variables.

Sixth, to effectively assess the impacts of TTF on use and user performance, six important steps followed in this study were identified. This sequential procedure forms the basis for a comprehensive, prescriptive, TTF evaluation framework, as demonstrated in Figure 11.3. This prescribed, diagnostic framework represents a pioneering methodological contribution, useful for the theorization of TTF, therefore addressing various important shortcomings[88] identified in previous TTF research.

[88] A detailed description of TTF research shortcomings is provided in Section 4.6 of Chapter 4.

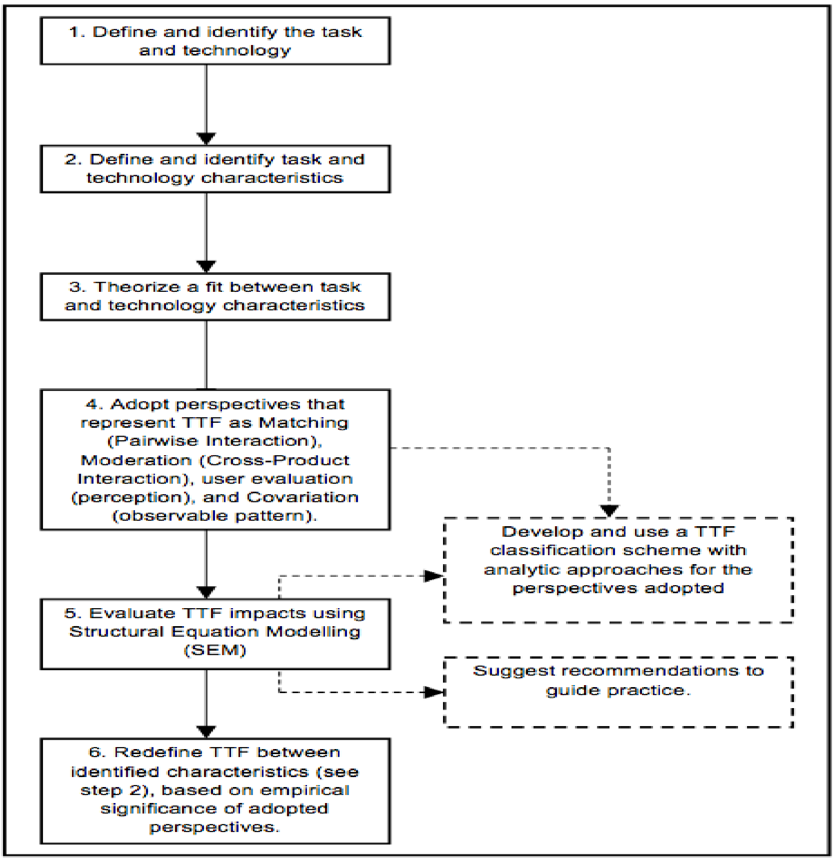

Figure 11.3. Proposed Task-Technology Fit (TTF) Framework

In steps 1 and 2, the task and technology, and their underlying characteristics, are identified. In step 3, the ‘fit’ between task and technology characteristics is theorized. In step 4, ‘fit’ perspectives (Venkatraman, 1989) representing matching, moderation (interaction), user evaluation (perception) and covariation (observable pattern) concepts, are adopted and used for empirical assessment. For the first time, the ‘fit’ perspectives of Matching, Moderation, Mediation and Covariation are adopted and used in a single study to examine TTF and its impacts on use and user performance. In step 5, TTF impacts on use and user performance are empirically assessed using Partial Least Squares – Structural Equation Modeling (PLS -SEM) (Hair et al., 2014) techniques. Uniquely, these techniques are applied to mHealth, generic health, TTF, and TPC research, simultaneously. Subsequent to steps 4 and 5, a classificatory scheme for the technical evaluation of TTF concepts is developed for the first time in TTF research, constituting an extended, novel, methodological contribution of this study. This derived classificatory scheme, uniquely developed for TTF study in IS research, is presented in Table 11.2, effectively extending and re-designing the original analytic schemes successfully implemented by Venkatraman (1989). This is therefore a schematic representation that signifies an explicit perspective-oriented approach to TTF analysis, and can be utilized as a high precision diagnostic tool.

Table 11.2. Task-Technology Fit (TTF) Classification Scheme				
	Perspectives			
Parameters	**Matching**	**Moderation**	**Mediation**	**Covariation**
Concept	Paired complementary task and technology characteristics.	Cross product of task and technology characteristics.	Intervening mechanism between task and technology characteristics and use and user performance.	Internally consistent co-alignment of task and technology characteristics.
Approach	• Selection	• Interaction	• User evaluation	• Systems
Type	• Computed	• Computed	• Perceived	• Observed
Analysis	• Matrix • PLS-SEM (moderator analysis) • Interaction plots	• Matrix • PLS-SEM (moderator analysis) • Interaction plots • Polynomial regression • Response Surface Methodology	• PLS-SEM (mediator analysis)	• PLS-SEM (confirmatory second-order factor analysis)
Configuration (Model Setup)	• Single Matched-Pairs • Multiple Matched-Pairs	• Single Cross-Product Interaction Pairs • Multiple Cross-Product Interaction Pairs	• Single Mediating Perceived Fit Dimensions • Multiple Mediating Perceived Fit Dimensions	• Multiple Reflective First-Order Factors as Reflective Indicators of Fit as a Second-Order Construct (Type II model setup)

Curiously, and despite its theoretical and practical significance, it must be recognized that to date, there has been no universally accepted TTF definition. This is despite various researchers (Goodhue et al., 1997; Dishaw, 1994, Dishaw and Strong, 1998) having attempted to adequately define [89] the construct. To define TTF, with its apparent complexity, the adoption and use of 'fit' perspectives to empirically assess its constituent characteristics and consequent impacts is of paramount importance, and must be acknowledged. As per step 6 (Figure 11.3), to extend previous efforts to capture this

[89] Please refer Table 4.1 in Chapter 4, for various definitions of TTF used in previous research.

nuanced phenomenon in IS research, the TTF construct must be defined in light of its apparent complexity. Furthermore, it is incumbent upon researchers to recognize that TTF is context-sensitive. In other words, task domains depend on the needs of particular users in specific contexts, for which support functions must be designed to optimize their experience using specific tools to perform specific tasks. As such, it would, therefore, be prudent and perhaps more sensible, to define TTF based on the significance of the perspectives adopted and used to examine its impacts on use and performance. For example, in this study, TTF, which was informed by the adopted 'fit' perspectives of Matching, Moderation, Mediation, and Covariation, and examined in the context of mHealth tool use and CHW performance, was found to have significant impacts on use and user performance.

Consequently, in the context of this study, TTF can and must be defined as **'a (1) matched pairwise, (2) cross-product interaction, (3) internally consistent, co-alignment, and (4) perceived intervening mechanism, that exists between determinant CHW needs and mHealth tool functions, and consequent use and user performance outcomes'**. In essence, TTF is only as good as the 'fit' perspective from which it is assessed in a particular context. Thus a more precise definition of TTF can only be derived from the 'fit' perspective that is under observation. This is of particular interest to researchers because unlike more conventional IS concepts that have been pre-defined based on theory a priori, TTF has to be first empirically assessed and can therefore be re-assessed as a re-definable construct after testing. This signifies the evolution of 'fit' conceptualization in TTF research. As a consequence, TTF can assume multiple formulations in various settings or user-environments. This realization lends credence to the critical importance of adopted 'fit' perspectives[90] in TTF research. As indicated earlier in this chapter, in the strategic management discipline, Venkatraman (1989) developed a framework of 'fit' perspectives each represented as conceptual models with corresponding analytical schemes. Similarly, Bergeron (2001) used empirical methodologies to compare multiple 'fit' perspectives. In retrospect, the implementation of these approaches set a precedent to be built upon in future research. For the first time, through the present study, multiple 'fit' perspectives were explicitly operationalized and tested in TTF research, in a manner that ensured theoretical and

[90] Please refer Section 4.6.4 for a detailed discussion of the importance of fit perspectives in TTF research.

empirical consistency. Venkatraman (1989) observed that 'fit' concepts were seldom tested in precisely the manner theorized (p. 438). This has long been a persistent TTF research shortcoming, which was addressed in this study.

11.4.3 Contributions to Practice

First, in Chapter 3, a quasi-experimental post-test was conducted to empirically examine CHW performance using mHealth tools compared to traditional paper-based systems. This provided evidence helpful to practitioners, constituting an approach with which to evaluate distinct intervention and control groups of users performing identical tasks using alternative technologies.

Second, in Chapters 6 to 9, the systematic assessment of TTF impacts was demonstrated by adopting nuanced perspectives with which to better articulate and explicate the complex phenomenon of 'fit', in order to evaluate numerous ways in which tool functions can meet user needs, and subsequently affect levels of use and user performance. This represents a versatile, evaluative, analytic tool with which practitioners can empirically assess the impacts of technology in any user environment, setting, or context, in which various tools or systems are used in the performance of a wide range of tasks. Moreover, using these 'fit' perspectives, technology designers can better anticipate user perceptions and needs to design consistent and responsive tool support functions for optimized use and user performance. This represents the multitude of ways in which practitioners can anticipate and envision the extent or degree of a 'fit' between user needs and tool functions, and effectively evaluate these mechanisms so as to better substantiate use and user performance effects. Consequently, practitioners would be better enabled to understand under what circumstances tool use and task performance can be enhanced, therefore placing greater emphasis on the more scientific, evidence-based, design of user-centric technologies.

Notably, time criticality fit is important for user performance, and to achieve this, mHealth tool designers should incorporate functional features such as event-trigger SMS alert messages to support tasks that require CHWs to better respond promptly e.g. during emergencies to promptly refer patients to hospitals or clinics for specialized care or treatment. Moreover, mobility-interdependence fit is important for use and user performance, and to achieve this, mHealth tool designers must incorporate support functions such as interactive transmission of voice and text, to complement tasks that require CHWs to process and share data with their community supervisors as they move to remote households to collect patient data. Furthermore, mobility-information dependency fit is important for user performance, and to achieve this, mHealth tool designers must incorporate support functions such as location-aware services e.g. localized data in real-time for access to inventory data on the location of supplies or equipment when on the move, to complement tasks that require CHW manoeuvrability. Equally important, information dependency time criticality fit is important for user performance, and to achieve this, mHealth tool designers can consider incorporating support functions event-trigger SMS alert messages, not only to enable emergency responses, but also to complement tasks that require CHWs to access household data at the point-of-care, in real-time. In addition to the design of functional support for tasks, practitioners should be acutely aware that users form perceptions of the 'fit' of tool functions to their needs, which can influence how they use the technology and perform their tasks. More positive CHW perceptions would be created by ensuring the design of functional support for time criticality, interdependence, and information dependency task needs.

Third, in Chapter 10, the importance of technology use, its precursors, and user performance impacts, was quantified. In addition to empirically assessing TTF and user performance, the importance of use as an outcome to be evaluated for tool or system design for practitioners, is therefore emphasized as an emergent priority for the design of more user-focused technologies. As such, it is therefore essential for practitioners to understand just how the use of 'fit-for-purpose' tools or systems eventually translates to user performance gains. In addition, facilitating conditions such as decision support, logistical support, user training, ease of access to supplies and equipment and information resources, and adequate mobile coverage during site-visits should be put in place to ease the burden of CHWs.

Fourth, across Chapters 6 to 10, links between TTF, use and its precursors, and user performance, were sequentially evaluated as important constructs in an overarching TPC model. This is a comprehensive analytic, diagnostic, approach useful for practitioners in gauging the specific mechanisms or processes through which technologies that are used in particular contexts or settings can impact the performance of tool or system users. The modeling of causal chain mechanisms represents a more thorough approach with which practitioners can more accurately pinpoint the impacts of tools or systems, and use adduced findings to enhance technology-enabled task performance through more data-driven design processes to improve task-fit and technology use.

11.4.4 Contributions to Context

First, in the present study, CHW mHealth projects implemented in peri-urban communities across five counties in the Kenyan context were evaluated in conjunction with the local government Ministry of Health (MOH) Division of Community Health Services (DCHS). These projects are aligned to regional and global health care initiatives including (1) the mHealth Alliance, (2) the Millennium Development Goals (MDGs), (3) the Global Health Workforce Alliance, and (4) the Frontline Health Workers Coalition.

Second, in Chapter 3, the performance of CHWs was assessed using a data-driven comparison of mHealth tools and traditional paper-based systems. This approach was devised to provide robust evidence of mHealth tool impacts on CHW perceptions of their performance in patient care delivery at the household level, in low-resource settings. CHW performance was evaluated largely in relation to the work function[91] of reporting, to for the first time, empirically demonstrate how through this function, CHWs at the frontlines of patient care in Kenya effectively act as a bridge between their respective communities and hospitals and clinics.

Third, in Chapters 6 to 9, the ‘fit’ between CHW tasks and mHealth technologies was evaluated, and its impacts on tool use and user task performance in low-resource settings assessed. Subsequent findings constitute substantive empirical evidence useful for a more nuanced understanding of the importance of what functional supporting technological requirements are most appropriate for CHW task needs in low-resource developing country contexts and settings. Moreover, the evidence uncovered in this study signifies the empirical substantiation of the technological support of CHWs at the point-of-care through mHealth tool use.

[91] Please refer Figure 2.2 of Section 2.6.1 in Chapter 2 for a detailed discussion of the role and primary responsibilities of CHWs.

Fourth, in Chapter 10, mHealth tool use, its determinants, and its consequent impacts, were evaluated as applied to the Kenyan context. The substantive findings of this study represent empirical evidence that is useful and practical for the enhanced understanding of what factors are the most significant determinants of mHealth tool use, what its functional role is within a healthcare ecosystem, and how it ultimately impacts CHW performance. For instance, along with their perception of a technology 'fit' to tasks, CHWs must also perceive that facilitating mechanisms are in place for effective tool to likely occur.

11.5 Future Research

First, a cross-sectional study design was used in this study. In future works, researchers may consider adopting supplementary longitudinal designs in order to examine and observe the long-term impacts of mHealth tool use on CHW performance outcomes, since this approach was not conducive to the scope of this study. Longitudinal studies using data forecasting techniques or phased approaches such as time-series design analysis among others, can be useful for additional, richer, insights into how TTF and other precursors influence use over an extended period of time, and as a methodological supplement to cross-sectional studies.

Second, four user-perceived fit dimensions, namely 'perceived time criticality fit', 'perceived interdependence fit', 'perceived mobility fit', and 'perceived information dependency fit', were empirically assessed in the present study. In future works, researchers must consider the development of additional variables to measure the user perception of a 'fit' between task and technology characteristics across a broader range of mHealth technology contexts, for comparison purposes.

Third, multiple 'fit' perspectives were adopted and used to examine TTF, but only a perceived TTF construct was examined in completing and extending the TPC model tested in Chapter 10. To further investigate TTF effects on user performance through use in future studies, researchers must consider the evaluation of multiple TTF perspectives within a TPC model. This approach can inform the development of an all-encompassing TPC theory, which would represent the logical, natural, next phase in the evolution of TPC research that is underpinned by TTF theory, and applied to a particular context.

Fourth, to effectively assess TTF impacts in alternate tool or system user environments, future researchers must consider replicating the conceptual models developed for this study in other settings, industries, or sectors that are technology-driven, and in which service delivery is technology-enabled. This represents a natural progression in TTF research, with potential far-reaching implications for industry, as it must be explicitly recognized that technology users in every conceivable setting or user environment would use particular tools or systems to perform a wide range of tasks. These users would, therefore, always have task needs that necessitate 'fit-for-purpose' responsive tool or system support functions.

Fifth, from a contextual perspective, mHealth tool impacts in the context of CHW performance in Kenya were empirically assessed in this study. Future researchers must consider the assessment of mHealth tool impacts in other low-resource settings so as to better understand and compare technology-enabled patient care in more widespread health contexts e.g. cross-country studies. This would allow for a quantitative comparison of impacts across varied mHealth ecosystems, thereby contributing towards enhancing on-going concerted efforts to ensure global best practices in the delivery of mHealth technology-enabled patient care. Future researchers can consider engaging with the literature in the domain of Information and Communication Technologies for Development (ICT4D) to investigate mHealth tool-enabled impacts, from the perspective of CHWs as participants at the "bottom of the pyramid". Future researchers could also consider impacts from the perspective of the patient. These could be useful alternative approaches to evaluating mHealth CHW initiatives.

11.6 Chapter Conclusion

As an examination of the impact of the mHealth tool on CHW performance, this study constitutes a significant contribution to an understanding of the mechanisms through which technology impacts user performance, with far reaching implications for research and practice. In this study, the substantive impacts of mHealth on CHW performance in low-resource settings was confirmed, as mHealth tool users were found to outperform traditional paper-based system users on the reporting of complete monitoring, prevention, and referral reports weekly in less time than their counterparts, and report significantly higher percentages of both timeous and complete monthly cases. In addition, it was found through the development and testing of a technology-to-performance chain model, that a task-fit is important to the use of the mHealth tool and the performance of CHWs. The characteristics of time criticality, and information dependency are especially considered as arguably the more important dimensions of ‘fit’, although interdependence, mobility, and information dependency, are considered as potentially critical, thus warranting further investigation. The findings of this study are essential to addressing the problem of mHealth project scalability by employing rigorous methodologies to provide robust evidence-based solutions. As a consequence of this study, researchers and practitioners can better understand and explain the mechanisms through which mobile technologies impact user performance in the healthcare context, and by extension, positively impact socio-economic development in low-resource settings.

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Appendix A Sampling

A.1 Dataset 1

Stratification (Daniel, 2012) was used to design the sampling frame for Dataset 1 (n = 312). This involves separation of the target population into mutually exclusive, homogenous segments (strata), from which a simple random sample is selected (p. 131). The target population comprised CHWs using mHealth tools[92] in peri-urban informal settlements. Community Health Units (CHUs) were identified from three counties, namely Siaya, Nandi, and Kilifi.

Operating under the auspices of the Government of Kenya (GoK) Ministry of Health (MOH), the Division of Community Health Services (DCHS) provided registers constituting lists from which a proportionate number of CHUs were systematically drawn. In addition, a proportionate number of participant CHWs was randomly selected from the selected CHUs. In total, 312 CHWs were sampled from CHUs across the identified counties.

The distribution (n = 312) of CHWs sampled from each CHU per county selected is detailed in Table A.1.

Table A.1. Sampling Frame (Dataset 1)

County	Community Health Workers (CHWs)	Community Health Units (CHUs)	CHWs per CHU
Siaya	120	11	11
Nandi	92	9	10
Kilifi	100	7	14

As suggested by Daniel (2012), the strata should not overlap, and together, should comprise the sample population. Moreover, the strata should comprise independent, mutually exclusive, homogenous sample subsets (p. 132). The strata, constituting the sampling frame used for this study, were evaluated for coverage biases (Daniel, 2012). In addition, to prevent 'over-coverage', 'under-coverage', and 'multiple-coverage' biases (Daniel, 2012, p. 28), CHUs identified were thoroughly screened. Moreover, several

[92] To the best of the researcher's knowledge, there were only three established CHW mHealth project sites in Kenya officially acknowledged by the Ministry of Health (MOH) Division of Community Health Services (DCHS), as at the time of field data collection for this study.

CHUs were identified across the counties selected, and CHWs were selected from various sites in these counties.

The sampling frame designed for Dataset 1 comprising 312 CHWs is depicted in Figure A.1.

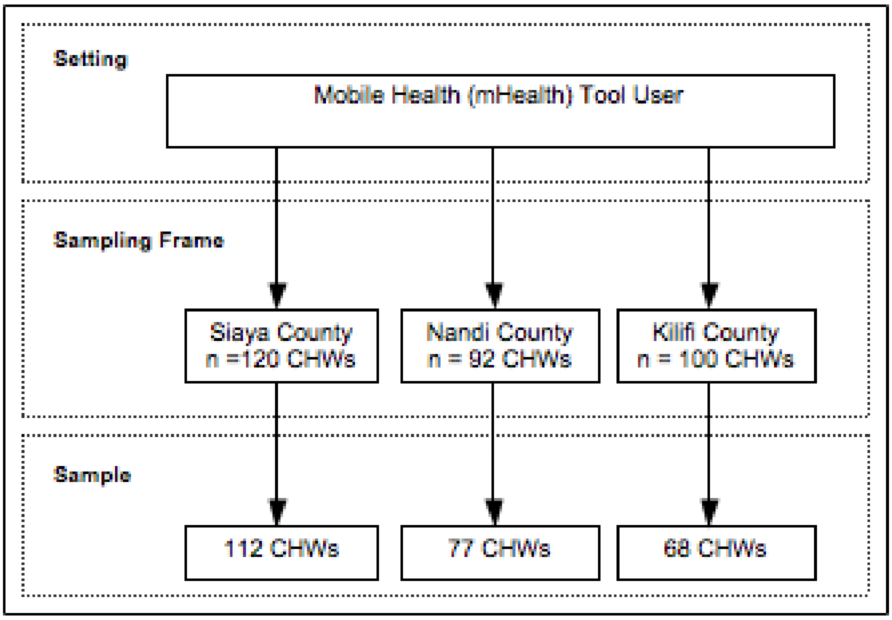

Figure A.1. Sample Design: Dataset 1 (n = 312) (mHealth Tool Users)

A.2 Dataset 2

Operating under the auspices of the Government of Kenya (GoK) Ministry of Health (MOH), the Division of Community Health Services (DCHS) provided registers constituting lists from which a proportionate number of CHUs were systematically drawn. In addition, a proportionate number of participant CHWs was randomly selected from the selected CHUs. In total, 312 CHWs were sampled from CHUs across the identified counties.

Stratification (Daniel, 2012) was also used to design the sampling frame for Dataset 2 (n = 375). The target population comprised CHWs using traditional paper-based systems in peri-urban informal settlements. CHUs were identified from two counties, namely Nairobi and Nakuru, also using Division of Community Health Services (DCHS) registers provided under the auspices of the Ministry of Health (MOH). To form the sampling frame, a proportionate number of CHWs was randomly from CHUs systematically drawn from across the identified counties.

The distribution (n =375) of CHWs sampled from each CHU per county selected is detailed in Table A.1.

Table A.2. Sampling Frame (Dataset 2)			
County	Community Health Workers (CHWs)	Community Health Units (CHUs)	CHWs per CHU
Nairobi	100	4	25
Nakuru	275	11	25

The CHUs, representing sampling frame strata, were also thoroughly screened for coverage biases.

The sampling frame designed for Dataset 2 comprising 375 CHWs is depicted in Figure A.2.

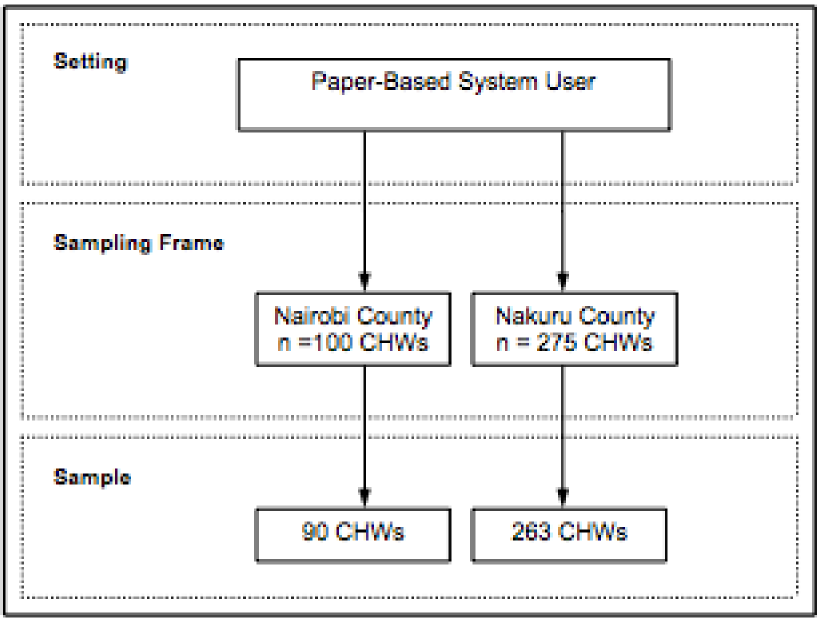

Figure A.2. Sample Design: Dataset 2 (n = 375) (Paper-Based System Users)

Appendix B Survey

B.1 Dataset 1

Survey design is used to generalize a sample to the target population, so that inferences can be made about respondent characteristics and orientations (Babbie, 2013, p. 229). A cross-sectional survey design was used to elicit data from CHWs using mHealth tools. This approach is used to describe a target population at a particular point in time (Pinsonneault and Kramer, 1993). A structured questionnaire was developed as the primary survey instrument of choice, and administered to CHWs using mHealth tools in the Siaya, Nandi, and Kilifi counties. Participating CHWs (n= 312) were contacted by telephone and invited to assemble at designated community health centres, where the structured questionnaire was administered to them. In each county, respondents were informed that their use of mHealth tools for patient care would be evaluated. In each county, assisted by one senior researcher, two public health specialists, a county officer, and a community field coordinator, the questionnaire was administered to participants. Moreover, in each county, CHWs assembled were verbally informed that participation was voluntary, confidential, and anonymous, without any penalties whatsoever. Furthermore, the CHWs assembled were not interfered with or coerced, and permission was ensured, such that completing the questionnaire was taken as their informed consent. The questionnaire did not necessitate translation, since the participating CHWs are English-speaking[93].

B.2 Dataset 2

A cross-sectional survey design was also used to elicit data from CHWs using traditional paper-based systems. A structured questionnaire was developed as a supplementary survey instrument and administered to CHWs in the Nairobi and Nakuru counties. Participating CHWs (n= 375) were also reached by telephone and invited to assemble at designated community health centres, where the structured questionnaire was administered to them. In each county, these respondents were informed that their performance using traditional paper-based systems for patient care would be evaluated. The questionnaire was administered to participants, also with the assistance of a senior

[93] English is the official spoken language in Kenya.

researcher, two public health specialists, a county officer, and community coordinator. Similarly, in the two counties, CHWs assembled were verbally informed that participation was voluntary, confidential, and anonymous, without any penalties whatsoever. Moreover, these assembled CHWs were not interfered with or coerced, and permission was ensured such that completing the questionnaire informed their consent. The questionnaire did not necessitate translation, since participants were English-speaking.

Appendix C Questionnaire

C.1 Primary (Dataset 1)

Questionnaire design involves two aspects (Saunders, Lewis, and Thornhill, 2012). First, respondents must decode questions in the manner intended by the researcher. Second, the researcher must decode answers in the manner intended by respondents (p. 429). A primary questionnaire twelve pages long and comprising six sections was designed for the present study. This questionnaire, used to survey mHealth tool users, was pretested for content validity (Leedy and Ormrod, 2013, p. 89), the extent to which instrument scale items and concepts correspond (Vanderstoep and Johnston, 2009, 59). First, questionnaire items were adapted from literature (Bourque and Clark, 1994). Second, the questionnaire was administered for pretesting by four academics, comprising expert researchers and social scientists, whose comments were incorporated. Third, the questionnaire was administered for pretesting by four practitioners, comprising consultants and public health specialists, whose comments were also incorporated. Saunders, Lewis and Thornhill (2012) suggested that to ensure content validity, expert panellists ought to be involved to evaluate whether items are essential, useful, or unnecessary (p. 429).

To ensure face validity (Leedy and Ormrod, 2013), a pilot study of thirteen CHWs using an mHealth tool was conducted. Their responses were useful for ascertaining the reliability of questionnaire instrument measures. The feedback obtained from these pilot testers was used to further refine the questionnaire prior to administering it to respondents. Face validity is the extent to which on the surface (Leedy and Ormrod, 2013), indicators are seemingly measures of their underlying constructs (Bhattacherjee, 2012). The pilot study was conducted to ensure that questionnaire items were comprehensible (Saunders et al., 2010, p. 452) and respondents followed instructions. The estimated time for respondents to complete the questionnaire was forty-five minutes. It was important to ensure that the full range of item scales in the questionnaire was used (Straub, 1989).

Bell (2010) suggested that a pilot study should capture (1) how long it takes respondents to complete the questionnaire, (2) whether respondents consider the instructions to be clear and concise, (3) which questions are ambiguous, and (4) which questions make respondents uncomfortable. To clearly and concisely explain the purpose and importance of the administered questionnaire (Saunders et al., 2012), an accompanying cover letter was attached (p. 446). In the letter, respondents were informed that their participation was voluntary. Dillman (2009) observed that an accompanying cover letter could improve the response rate. As suggested by Saunders, Lewis and Thornhill (2012), the respondents were notified both verbally and in writing, that completing and returning the questionnaire would be taken as their informed consent. Moreover, as recommended by Israel and Hay (2006), respondents must be informed of methods, demands, risks, inconveniences, and the provision of aggregated results of the study at their convenience (p. 61).

C.2 Primary (Dataset 2)

A supplementary questionnaire three pages long and comprising three sections, was designed. This questionnaire, for paper-based system users, was pretested to ensure content validity. First, the questionnaire was administered for pretesting by four academics, comprising expert researchers and social scientists, whose comments were incorporated. Second, the questionnaire was administered for pretesting by four practitioners, comprising consultants and public health specialists, whose comments were incorporated. To ensure face validity (Leedy and Ormrod, 2013), a pilot study of fifteen CHWs using a paper-based system was conducted, and their input used to further refine the questionnaire. The estimated time for respondents to complete the questionnaire was twenty minutes. To define the purpose and importance of the administered questionnaire (Saunders et al., 2012), there was an accompanying cover letter (p. 446). It indicated that participation was voluntary, and completion of the questionnaire would be taken as informed consent.

Appendix D Data Screening[94]

D.1 Missing Values (Dataset 1)

For Dataset 1, the survey instrument was administered to 312 respondents, from which 257 responses were obtained. First, data were screened by observing (1) the number of variables with missing values for each case, and (2) the number of cases with missing values for each variable. Second, exceptionally high levels of missing data per case or observation were identified. Hair, Black, Babin, and Anderson (2010) suggested that less than 10% of cases should contain missing data. Moreover, cases with no missing data are sufficient for analysis when replacement values are not substituted (imputed) for the missing data (p. 47). Cases containing large amounts of missing data or extreme response sets were excluded, after which 201 (n = 201) usable mHealth tool user responses were retained for subsequent analyses. Hair, Black, Babin, and Anderson (2010) suggested that before diagnosing random patterns in the data, exclusion of offending cases or variables with excessive missing values should be considered. Moreover, excluding these cases or variables substantially reduces the extent of missing data (p. 48). For the remaining cases, substitution imputation was used to replace missing data with the series mean for each set of constructs, and ensure complete data (Hair et al., 2010, p. 53). The missing values replaced with the series mean for task characteristics, are shown in Table D.1.

[94] Data collected were captured in Microsoft (MS) Excel then exported to SPSS for screening purposes.

Table D.1. Missing Data: Task Characteristics			
Construct	Measure	Missing Values	Replaced (Series Mean)
Time Criticality	TC 1	3	Yes
	TC 2	4	Yes
	TC 3	2	Yes
	TC 4	2	Yes
	TC 5	3	Yes
	TC 6	4	Yes
Interdependence	IN 1	5	Yes
	IN 2	10	Yes
	IN 3	7	Yes
	IN 4	7	Yes
	IN 5	7	Yes
Mobility	MP 1 (M)	11	Yes
	MP 1 (P)	9	Yes
	MP 1 (R)	2	Yes
	M (V) 1	6	Yes
	M (V) 2	5	Yes
	M (V) 3	6	Yes
	M (V) 4	8	Yes
Information Dependence	ID 1	6	Yes
	ID 2	6	Yes
	ID 3	3	Yes
Total		**127**	

The missing values replaced with the series mean for technology characteristics, are shown in Table D.2.

Table D.2. Missing Data: Technology Characteristics			
Construct	Item	Missing Values	Replaced (Series Mean)
Time Criticality Support	TCS 1	3	Yes
	TCS 2	7	Yes
	TCS 3	6	Yes
Interdependence Support	IS 1	5	Yes
	IS 2	3	Yes
	IS 3	4	Yes
	IS 4	5	Yes
Mobility Support	MS 1	5	Yes
	MS 2	6	Yes
	MS 3	3	Yes
	MS 4	5	Yes
Information Dependence Support	IDS 1	4	Yes
	IDS 2	2	Yes
	IDS 3	3	Yes
Total		**61**	

The missing values replaced with the series mean for perceived TTF, are shown in Table D.3.

Table D.3. Missing Data: Perceived Task-Technology Fit (TTF)			
Construct	Item	Missing Values	Replaced (Series Mean)
Perceived Time Criticality Fit	PTCF 1	5	Yes
	PTCF 2	3	Yes
	PTCF 3	6	Yes
	PTCF 4	7	No
Perceived Interdependence Fit	PIF 1	8	Yes
	PIF 2	7	Yes
	PIF 3	11	Yes
	PIF 4	8	Yes
Perceived Mobility Fit	PMF 1	9	Yes
	PMF 2	10	Yes
	PMF 3	10	Yes
	PMF 4	4	Yes
Perceived Information Dependence Fit	PIDF 1	5	Yes
	PIDF 2	10	Yes
	PIDF 3	13	Yes
	PIDF 4	0	Yes
Total		**116**	

The missing values replaced with the series mean for technology characteristics, are shown in Table D.4.

Table D.4. Missing Data: Technology Use and Precursors			
Construct	Item	Missing Values	Replaced (Series Mean)
Use	U 1 (F)	3	Yes
	U 2 (Du)	2	Yes
	U 3 (De)	4	Yes
	U 4 (De)	5	Yes
	U 5 (De)	2	Yes
Affect Toward Using	ATU 1	0	Yes
	ATU 2	5	Yes
	ATU 3	5	Yes
	ATU 4	4	Yes
	ATU 5	4	Yes
Facilitating Conditions	FC 1	2	Yes
	FC 2	4	Yes
	FC 3	6	Yes
	FC 4	7	Yes
Total		**53**	Yes

The missing values replaced with the series mean for user performance, are shown in Table D.5.

Table D.5. Missing Data: User Performance			
Construct	Item	Missing Values	Replaced (Series Mean)
User Performance	UP 1 (PUP)	3	Yes
	UP 2 (PUP)	5	Yes
	UP 3 (PUP)	7	Yes
	UP 4 (PUP)	4	Yes
	UP 5 (PUP)	5	Yes
	UP 6 (PUP)	4	Yes
	UP 7 (PUP)	3	Yes
	UP 8 (PUP)	4	Yes
	UP 1 (CHWRP)	11	Yes
	UP 2 (CHWRP)	5	Yes
	UP 9 (CHWRP)	43	Yes
	UP 10 (CHWRP)	37	Yes
	UP 11 (CHWRP)	13	Yes
Total		**144**	Yes

D.2 Outlier Detection (Dataset 1)

Dataset 1 was screened for potential outliers using univariate detection (Hair et al., 2010). Univariate detection involves (1) converting data into standardized (z) scores, and (2) designating potential outliers. Observations for each variable were examined and cases falling at the outer (high or low) ranges of the distribution were identified as potential outliers (Hair et al., 2010 p. 66). For larger samples (80 or more observations), a z score of up to 4 should be established to ensure identification of unusually high or low values on each item compared to other cases (p. 67). The observations **64**, **138**, **154**, **161**, and **204**, exceeded the threshold value of standardized (z) scores for each variable. However, none were so extreme as to adversely affect any of the overall variable measures such as the mean or standard deviation. The five observations were noted to evaluate whether they would be subsequently detected. Dataset 1 was screened for potential outliers using bivariate detection (Hair et al., 2010). Using scatterplots, specific relationships between variables are assessed, and cases outside the range of observations in isolation, are potential outliers (p. 66). Four scatterplots were formed for select CHW characteristics and user performance variables. Scatterplots for respective experience as a CHW and education level with facilitating conditions and user performance, were examined to identify potential outliers. Subsequently, these scatterplots showed that observations **64**, **138**, **154**, and **161** were isolated points, corroborating univariate outlier detection used previously. Hair, Black, Babin, and Anderson (2010) recommended that because scatterplots could increase depending on the number of variables, using bivariate methods to detect outliers in particular datasets should be restricted to specific relationships (p. 66).

Despite the use of univariate and bivariate detection to detect potential outliers, no observations in the sample population were sufficiently extreme to be considered unrepresentative. Consequently, the potential outliers detected were retained for further analyses.

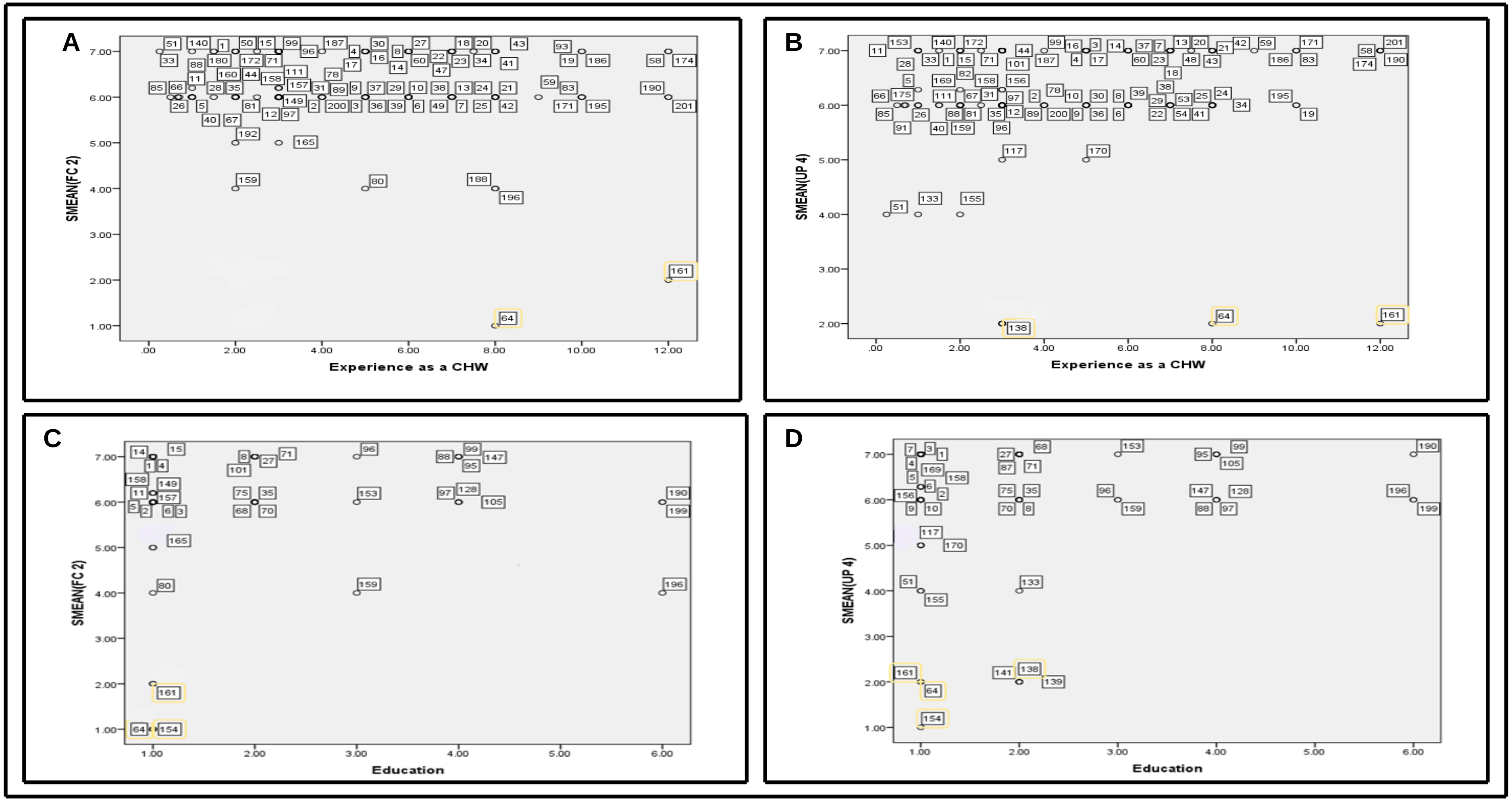

Figure D.1. Scatterplot for Bivariate Detection of Outliers: Dataset 1 (n=201)

D.3 Missing Values (Dataset 2)

The survey instrument for Dataset 2 was administered to 375 respondents, from which 353 responses were obtained. For the remaining cases, substitution imputation (Hair et al., 2010) was used. To ensure a complete dataset, missing values were replaced with the series mean for each variable (p. 53). These missing values with the series mean are shown in Table D.6.

Table D.6. Missing Data: Dataset 2

Construct	Item	Missing Values	Replaced (Series Mean)
User Performance	UP 1 (PUP)	1	Yes
	UP 2 (PUP)	0	Yes
	UP 3 (PUP)	1	Yes
	UP 4 (PUP)	0	Yes
	UP 5 (PUP)	1	Yes
	UP 6 (PUP)	0	Yes
	UP 7 (PUP)	0	Yes
	UP 8 (PUP)	0	Yes
	UP 1 (CHWRP)	1	Yes
	UP 2 (CHWRP)	0	Yes
	UP 9 (CHWRP)	31	Yes
	UP 10 (CHWRP)	29	Yes
	UP 11 (CHWRP)	2	Yes
Total		**66**	Yes

D.4 Outlier Detection (Dataset 2)

Dataset 2 was screened for potential outliers using univariate detection (Hair et al., 2010). Observations for each variable were examined, and cases falling at the outer ranges (high or low) of the distribution were identified as potential outliers (Hair et al., 2010). The observations **8**, **29**, and **45** exceeded the threshold value of standardized (z) scores for each variable. However, none were so extreme as to adversely affect overall variable measures such as the mean or standard deviation. The observations were noted for further analyses. Dataset 2 was screened for potential outliers using bivariate detection (Hair et al., 2010, p. 66). Two scatterplots were formed for select CHW and CHW performance characteristics. Scatterplots for respective age and experience as a CHW, with user performance, were examined to identify potential outliers. These scatterplots showed that only observation **8,** identified previously, was isolated. Despite using univariate and bivariate methods to detect potential outliers, no observations in the sample population were sufficiently extreme to be considered unrepresentative. Consequently, the potential outliers detected were retained for further analyses.

D.5 Common Method Bias

Since data for variables were obtained from single respondents using a cross-sectional survey, common method variance may affect postulated structural path model relationships (Sattler et al., 2010). A Harman's (1976) single-factor test (Podsakoff and Organ, 1986) was used to test for common method bias by subjecting variables to Exploratory Factor Analysis (EFA). Common method bias is detected if a single factor accounts for most (> 50%) of the variance in predictor and criteria variables. The first and last factors accounted for 18.8% and 2.1% of overall variance respectively, thereby negating any risk of common method bias. In addition, Average Variance Extracted (AVE) square root values of 0.90 or lower (Bagozzi, Yi and Phillips, 1991) were obtained. Moreover, inter-construct correlations below this threshold were observed. Therefore, common method bias was not detected.

Appendix E Constructs

E.1 Task-Technology Fit (TTF)

In Chapter 4, the constructs used to evaluate CHW task and mHealth tool characteristics were identified. These constructs were used to operationalize TTF, comprising (1) the task, (2) the technology, and (3) the 'fit' between the task and the technology. The task has characteristics or features that reflect user needs (Goodhue et al., 1997). Four task characteristics that reflected CHW needs were identified. First, time criticality is the need to perform the task urgently (Gebauer and Tang, 2007). Second, interdependence is the need to co-operate with others (Hsiao and Chen, 2012). Third, mobility is the need to move form one location to another (Junglas et al., 2009). Fourth, information dependency is the need to access data (Yuan et al., 2010). The CHW task characteristics comprised twenty-one seven-point Likert scale item measures. The scale items used to measure task characteristics are listed in Table E.1.

Table E.1. Measures: Task Characteristics			
Variable	Item	Statement	Source
Time Criticality [a]	TC 1	It is very important for me to start my tasks on time.	Yuan, Archer, Connelly and Zheng (2010)
	TC 2	It is very important for me to complete my tasks on time.	Yuan, Archer, Connelly and Zheng (2010)
	TC 3	It is very important for me to start my tasks as soon as possible.	Yuan, Archer, Connelly and Zheng (2010)
	TC 4	It is very important for me to complete my tasks as soon as possible.	Yuan, Archer, Connelly and Zheng (2010)
	TC 5	It is very important for me to take immediate action.	Gebauer and Tang (2007)
	TC 6	It is very important for me to promptly respond to emergencies.	Gebauer and Tang (2007)
Interdependence [a]	IN 1	I often need to complete my tasks with co-workers.	Yuan, Archer, Connelly and Zheng (2010)
	IN 2	I often need to share information with co-workers.	Jarvenpaa and Staples (2000), Teo and Men (2008)
	IN 3	I often need to rely on the work of other CHWs.	Gebauer and Tang (2007)
	IN 4	I often need to use information received from co-workers.	Jarvenpaa and Staples (2000), Teo and Men (2008)
	IN 5	I often need to depend on the efforts of other CHWs.	Jarvenpaa and Staples (2000), Teo and Men (2008)
Mobility [b]	Do you perform the following tasks at one or several locations?		Yuan, Archer, Connelly and Zheng (2010)
	M (V) 1	Monitoring	
	M (V) 2	Prevention	

	M (V) 3	Referral	
Information Dependency [b]	ID 1	I often need to depend on information on my current location.	Yuan, Archer, Connelly and Zheng (2010)
	ID 2	I often need to depend on information on the location of supplies.	Yuan, Archer, Connelly and Zheng (2010)
	ID 3	I often need to depend on information on the location of households.	Yuan, Archer, Connelly and Zheng (2010)

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

b = Measured on 6-point scale 1 = I perform my tasks in the same location to 6 = I perform my tasks in any given location where services are required.

The technology has characteristics or features that reflect supporting tool functions (Dishaw and Strong, 1998b). Four technology characteristics, reflecting mHealth tool functions, were identified. First, time criticality support is the tool function designed to support the need to respond urgently (Liang and Wei, 2004). Second, interdependence support is the tool function designed to support the need to co-operate with others (Hsiao and Chen, 2012). Third, mobility support is the tool function designed to support the need to move from one location to another (Junglas et al., 2008). Fourth, information dependency support is the tool function designed to support the need to access information (Yuan et al., 2010). The mHealth technology characteristics comprised fourteen seven-point Likert scale item measures. The scale items used to measure technology characteristics are listed in Table E.2.

Table E.2. Technology Characteristics

Variable	Item	Statement	Source
Time Criticality Support	TCS 1	The mHealth tool works well in providing timely notification of required urgent actions.	Wixom and Todd (2005)
	TCS 2	The mHealth tool effectively responds to my requests quickly.	
	TCS 3	The mHealth tool notifies me of emergencies in a timely manner.	
Interdependence Support	IS 1	The makes it easy to share information with others.	Goodhue (1992), Wixom and Todd (2005)
	IS 2	The mHealth tool effectively compiles data from co-workers.	
	IS 3	The mHealth tool effectively pulls together data from co-workers.	
	IS 4	The mHealth tool effectively integrates data from co-workers.	
Mobility Support	MS 1	The mHealth tool effectively responds to changes in location.	Wixom and Todd (2005)
	MS 2	The mHealth tool operates reliably as I move to different places.	
	MS 3	The mHealth tool flexibly adjusts as I move from one place to another.	
	MS 4	The mHealth tool effectively adapts to my movement from one	

		place to another.	
Information Dependency Support	IDS 1	The mHealth tool easily provides information on my current location.	Dishaw (1994), Wixom and Todd (2005), Jarvenpaa and Staples (2000)
	IDS 2	The mHealth tool makes information on the location of households very accessible.	
	IDS 3	The mHealth tool makes information on the location of supplies readily accessible.	

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

The ‘fit’ construct has been defined as the degree to which users perceive that the technology meets their task requirements (Nance, 1992). Four perceived ‘fit’ dimensions were identified. Perceived time criticality fit is the degree to which mHealth tool functions meet the need to perform the task urgently. Perceived interdependence fit is the degree to which mHealth tool functions meet the need to co-operate with others. Perceived mobility fit is the degree to which mHealth tool functions meet the need to move from one location to another. Perceived information dependency fit is degree to which mHealth tool functions meet the need to access data. The perceived ‘fit’ dimension characteristics comprised sixteen seven-point Likert scale items measures. The scale items used to measure perceived fit are listed in Table E.3.

Table E.3. Perceived Fit

Variable	Item	Statement	Source
Perceived Time Criticality Fit	PTCF 1	The mHealth tool supports me in starting my tasks on time.	Junglas, Abraham and Ives (2009)
	PTCF 2	The mHealth tool supports me in finishing my tasks on time.	
	PTCF 3	The mHealth tool supports me during urgent interventions.	
	PTCF 4	The mHealth tool supports me in promptly responding to emergencies.	
Perceived Interdependence Fit	PIF 1	The mHealth tool supports me in completing tasks with co-workers.	Junglas, Abraham and Ives (2009)
	PIF 2	The mHealth tool supports me in information sharing with co-workers.	
	PIF 3	The mHealth tool supports me in working with other CHWs.	
	PIF 4	The mHealth tool supports me in receiving information from co-workers.	
Perceived Mobility Fit	PMF 1	The mHealth tool supports me in performing tasks at several locations.	Junglas, Abraham and Ives (2009)
	PMF 2	The mHealth tool supports me in working away from just one place for long periods.	
	PMF 3	The mHealth tool supports me in working away form my Community Unit (CU).	
	PMF 4	The mHealth tool supports me in travelling to remote locations to perform tasks.	
Information Dependency Fit	PIDF 1	The mHealth tool supports me in accessing information on my current location.	Dishaw (1994), Junglas, Abraham and Ives (2009)
	PIDF 2	The mHealth tool supports me in accessing information on the location of	

		households.	
	PIDF 3	The mHealth tool supports me in accessing information on the location of supplies.	
	PIDF 4	The mHealth tool supports me in accessing information on the locations I travel to.	

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

E.2 Use

Use is the extent to which users perceive that they depend on the technology to perform the task (Goodhue and Thompson, 1995). Use as technology dependence, comprised three seven-point Likert scale item measures. The scale items used to measure use as technology dependence are listed in Table E.4.

Table E.4. Use

Variable	Item	Statement	Source
Use	U 1	I am very dependent on the mHealth tool to perform tasks.	Junglas, Abraham and Ives (2009)
	U 2	My work is dependent on using the mHealth tool to perform tasks.	
	U 3	Using the mHealth tool allows me to do more than would be possible without it.	

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

E.3 User Performance

User performance is defined as the perceived effectiveness (Torkzadeh and Doll, 1999), efficiency (Hou, 2012), and quality (Junglas et al., 2009), of task completion when using the technology. User performance comprised eight seven-point Likert scale item measures. The scale items used to measure perceived user performance, are listed in Table E.5.

Table E.5. User Performance

Variable	Item	Statement	Source
User Performance	UP 1	The mHealth tool increases my productivity.	Torkzadeh and Doll (1999), Junglas et al., (2009), Hou (2012)
	UP 2	The mHealth tool increases my effectiveness with patients.	
	UP 3	The mHealth tool increases my quality of patient care.	
	UP 4	The mHealth tool system saves me time.	
	UP 5	The mHealth tool system enables me to complete tasks more quickly.	
	UP 6	Using the mHealth tool improves my effectiveness in completing	

		tasks.	
	UP 7	The mHealth tool improves the quality of my tasks.	
	UP 8	The mHealth tool decreases my reporting errors.	

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

E.4 Precursors of Use

There are two precursors linked to technology use in this study. First, facilitating conditions are support factors in the user environment that are conducive to technology use (Thompson et al., 1991). Facilitating conditions comprised four seven-point Likert scale item measures. Second, affect toward use is the extent to which the user has a linking for the technology (Compeau et al., 1999). Affect toward use comprised four seven-point Likert scale item measures. The scale items used to measure precursors of use are listed in Table E.6.

Table E.6. Precursors of Use

Variable	Item	Statement	Source
Facilitating Conditions	FC 1	I have the resources required to use the mHealth tool.	Taylor and Todd (1995)
	FC 2	I have the knowledge required to use the mHealth tool.	
	FC 3	With the required training, it would be easy for me to use the mHealth tool.	
	FC 4	The mHealth tool does not complement paper-based systems I use.	
Affect Toward Use	ATU 1	I like using the mHealth tool.	Compeau and Higgins (1995), Compeau, Higgins and Huff (1999)
	ATU 2	I look forward to using the mHealth tool.	
	ATU 3	Using the mHealth tool is frustrating.	
	ATU 4	Once I start using the mHealth tool, I find it hard to stop.	
	ATU 5	I get bored quickly when using the mHealth tool.	

a = Measured on 7-point scale 1 = Strongly Disagree to 7 = Strongly Agree

Appendix F Multi-Collinearity (The Task-Technology Fit Model)

Prior to analyses, multiple regressions were run to check TTF measures for collinearity (Hair et al., 2014).

Table F.1. Collinearity: Task-Technology Fit (TTF)					
First Set			Second Set		
Criterion: Use			**Criterion: User Performance**		
Predictor	**Tolerance**	**VIF**	**Predictor**	**Tolerance**	**VIF**
Time Criticality	0.809	1.236	*Time Criticality*	0.809	1.236
Interdependence	0.803	1.245	*Interdependence*	0.803	1.245
Mobility (Variety)	0.880	1.137	*Mobility*	0.880	1.137
Mobility (Proximity)	0.832	1.202		0.832	1.202
Information Dependence	0.861	1.162	*Information Dependence*	0.861	1.162
Time Criticality Support	0.663	1.509	*Time Criticality Support*	0.663	1.509
Interdependence Support	0.555	1.802	*Interdependence Support*	0.555	1.802
Mobility Support	0.686	1.458	*Mobility Support*	0.686	1.458
Information Dependence Support	0.636	1.572	*Information Dependence Support*	0.636	1.572
Perceived Time Criticality Fit	0.550	1.819	*Perceived Time Criticality Fit*	0.550	1.819
Perceived Interdependence Fit	0.528	1.895	*Perceived Interdependence Fit*	0.528	1.895
Perceived Mobility Fit	0.724	1.382	*Perceived Mobility Fit*	0.724	1.382
Perceived Information Dependence Fit	0.634	1.578	*Perceived Information Dependence Fit*	0.634	1.578

The tolerance values were above 0.20, and the VIF values below 5. Thus collinearity was not considered a concern (Hair et al., 2011).

Appendix G Reliability and Validity

A Partial Least Squares – Structural Equation Modeling (PLS – SEM) algorithm was run to calculate the parameter estimates of measurement model constructs. Confirmatory Factor Analysis (CFA) was conducted to assess[95] construct measures for their internal consistency reliability, convergent validity, and discriminant validity.

G.1 Internal Consistency Reliability[96] and Convergent Validity

Results of evaluation of task characteristics for construct reliability and validity are shown in Table G.1.

Table G.1. Task Characteristics: Internal Consistency Reliability and Convergent Validity

Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
Time Criticality	TC3	0.826	0.803	0.582
	TC4	0.587		
	TC5	0.848		
Interdependence	I 1	0.772	0.796	0.662
	I 4	0.853		
Mobility (Variety)	M (V) 1	0.816	0.842	0.645
	M (V) 2	0.625		
	M (V) 3	0.938		
Mobility (Proximity)	M (P) 1	1.000	1.000	1.000
Information Dependency	ID 1	0.660	0.774	0.536
	ID 1	0.713		
	ID 1	0.814		

Results of evaluation of technology characteristics for construct reliability and validity are shown in Table G.2.

[95] This process is described as model validation, an attempt to ascertain whether the measurement model fulfils the quality criteria for empirical study (Urbach and Ahlemann, 2010, p. 18).

[96] The traditional criterion used to determine internal consistency has long been Cronbach's alpha. However, Cronbach's alpha is sensitive to the number of items in the scale and tends to underestimate the internal consistency reliability of a construct. As such, an alternative measure, composite reliability (p_c) is preferred for PLS-SEM (Hair et al., 2014).

Table G.2. Technology Characteristics: Internal Consistency Reliability and Convergent Validity				
Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
Time Criticality Support	TCS 1	0.685	0.800	0.573
	TCS 2	0.828		
	TCS 3	0.752		
Interdependence Support	IS 1	0.772	0.809	0.517
	IS 2	0.798		
	IS 3	0.662		
	IS 4	0.631		
Mobility Support	MS 1	0.803	0.803	0.576
	MS 2	0.707		
	MS 3	0.765		
Information Dependency Support	IDS 1	0.726	0.828	0.617
	IDS 2	0.851		
	IDS 3	0.773		

Results of evaluation of the perceived fit dimensions for construct reliability and validity are shown in Table G.3.

Table G.3. Perceived Fit: Internal Consistency Reliability and Convergent Validity				
Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
Perceived Time Criticality Fit	PTCF 1	0.796	0.829	0.618
	PTCF 2	0.812		
	PTCF 3	0.747		
Perceived Interdependence Fit	PIF 1	0.747	0.841	0.570
	PIF 2	0.825		
	PIF 3	0.747		
	PIF 4	0.694		
Perceived Mobility Fit	PMF 1	0.729	0.831	0.552
	PMF 2	0.820		
	PMF 3	0.733		
	PMF 4	0.683		
Perceived Information Dependency Fit	PIDF 1	0.779	0.795	0.568
	PIDF 2	0.855		
	PIDF 3	0.606		

Results of evaluation of use measures for construct reliability and validity are shown in Table G.4.

Table G.4. Use: Internal Consistency Reliability and Convergent Validity				
Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
Use (Frequency)	U (F) 1	1.000	1.000	1.000
Use (Duration)	U (DU)	1.000	1.000	1.000
Use (Dependence)	U (DE) 1	0.679	0.770	0.528
	U (DE) 2	0.751		
	U (DE) 3	0.747		

Results of evaluation of user performance measures for construct reliability and validity are shown in Table G.5.

Table G.5. User Performance: Internal Consistency Reliability and Convergent Validity				
Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
User Performance	UP 2	0.786	0.865	0.616
	UP 4	0.750		
	UP 6	0.789		
	UP 7	0.813		

Results of evaluation of use precursor measures for construct reliability and validity are shown in Table G.6.

Table G.6. Precursors of Use: Internal Consistency Reliability and Convergent Validity				
Latent Variable	Indicators	Outer Loadings	Composite Reliability (p_c)	AVE
Facilitating Conditions	FC 1	0.669	0.764	0.524
	FC 2	0.854		
	FC 3	0.628		
Affect Toward Use	ATU 1	0.868	0.777	0.637
	ATU 2	0.721		

The criteria that were used to evaluate the reliability and validity of measurement model constructs are summarized in Table G.7.

Table G.7. Criteria for Construct Reliability and Validity	
Parameter	Condition
Internal Consistency Reliability	• Composite reliability (p_c) should exceed 0.708 (in exploratory research, values between 0.60 and 0.70 are acceptable).
Indicator Reliability	• The indicator's outer loadings should exceed 0.708. Indicators with outer loadings between 0.40 and 0.70 should be considered for removal only if the deletion improves the composite reliability and Average Variance Extracted (AVE).
Convergent Validity	• The Average Variance Extracted (AVE) should exceed 0.50.
Discriminant Validity	• An indicator's outer loadings on a construct should exceed all cross-loadings with other constructs. • The square root of the AVE of each construct should be higher than its highest correlation with any other construct (Fornell-Larcker criterion). • Each pair of construct must not exceed the $HTMT_{.90}$ criterion i.e. 0.90

To satisfy the criteria for evaluating construct reliability and validity, specific indicators may be excluded (Hair et al., 2014). However, the exclusion of one or more of these indicators should improve reliability or discriminant validity without diminishing content validity (p. 107).

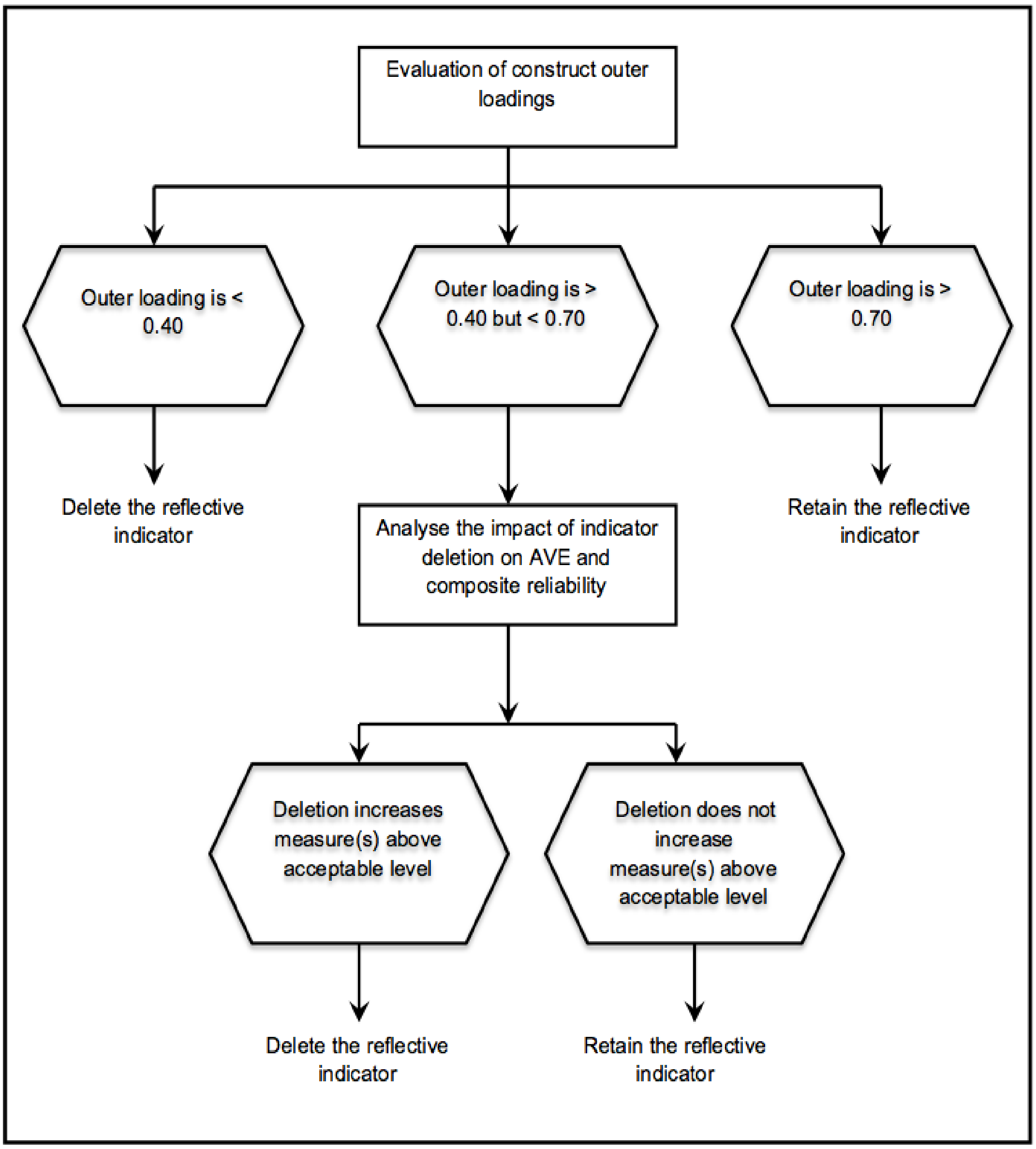

Figure G.1. Outer Loadings: Evaluation Process (Hair, Hult, Ringle and Sarstedt, 2014, p. 104)

The convergent validity of a construct is assessed using the AVE, a common measure defined as the grand mean of squared loadings of indicators, associated with the construct, or sum of squared loadings divided by the number of indicators (Hair et al., 2014). An AVE value above 0.50 or higher indicates that on average, the construct explains over half of the variance of its indicators. An AVE below 0.50 indicates that on average, there is greater error in the items than the variance explained by the construct (p. 103).

Measurement model construct indicators that did not meet the internal consistency reliability and convergent validity criteria (Figure G.1) detailed in Table G.7, are summarized in Table G.8.

Table G.8. Construct Indicators			
Latent Variable	Number of Original Indicators	Number of Indicators Retained	Indicators Excluded
Time Criticality	6	3	TC 1
			TC 2
			TC 6
Interdependence	4	2	INT 2
			INT 3
Mobility (Proximity)	4	1	M (P) 1
			M (P) 2
			M (P) 3
Mobility Support	4	3	MS 4
Perceived Time Criticality Fit	4	3	PTCF 4
Perceived Information Dependency Fit	4	3	PIDF 4
Facilitating Conditions	4	3	FC 4
Affect Toward Use	5	2	ATU 3
			ATU 4
			ATU 5
User Performance	8	4	UP 1
			UP 3
			UP 5
			UP 8

Legend: TC = Time Criticality, INT = Interdependence, M (P) = Mobility (Proximity), MS = Mobility Support (MS), PTCF = Perceived Time Criticality Fit, PIDF = Perceived Information Dependency Fit, FC = Facilitating Conditions, ATU = Affect Toward Use, UP = User Performance

G.2 Discriminant Validity

There are two ways in which discriminant validity can be evaluated (Hair et al., 2014, p. 104). First, it is evaluated by examining the cross loadings of indicators. An indicator's outer loading on the associated construct should exceed all of its loadings on other constructs (Hair et al., 2011). Second, it is evaluated using the Fornell-Larcker criterion (Fornell and Larcker, 1981), used to compare the square root of AVE values with latent variable correlations (Hair et al., 2014, p. 105). Construct cross-loadings and Fornell-Larcker criterion results are shown in Tables G.9 and G.10 respectively.

Table G.9. Cross-Loadings

	TC	I	M (P)	M (V)	ID	TCS	IS	MS	IDS	PTCF	PIF	PMF	PIDF	ATU	FC	U (De)	U (Du)	U (F)	UP
TC 3	**0.826**	0.247	0.168	0.146	0.205	0.273	0.233	0.177	0.124	0.281	0.259	0.153	0.204	0.254	0.284	0.072	0.115	0.139	0.305
TC 4	**0.590**	0.237	0.166	0.036	0.160	0.013	0.031	0.056	0.058	0.136	0.150	0.090	0.050	0.186	0.127	0.045	-0.010	0.013	0.120
TC 5	**0.846**	0.188	0.088	0.127	0.157	0.158	0.155	0.188	0.130	0.294	0.140	0.093	0.029	0.287	0.305	0.234	0.079	0.203	0.278
I 1	0.253	**0.768**	0.207	0.037	0.183	0.051	0.180	0.145	0.155	0.221	0.273	0.061	0.229	0.073	0.125	0.061	0.107	-0.011	0.098
I 4	0.200	**0.856**	0.006	0.032	0.145	0.173	0.194	0.071	0.046	0.103	0.261	0.008	0.173	0.036	0.091	0.106	0.079	-0.065	0.094
M (V) 1	0.091	0.062	**0.819**	0.142	0.159	0.082	0.110	0.113	0.074	0.078	0.141	0.322	0.089	-0.092	0.084	0.033	0.006	0.017	0.045
M (V) 2	0.135	0.170	**0.640**	0.226	0.040	0.039	0.112	0.103	0.012	0.140	0.058	0.244	-0.008	0.027	0.052	-0.004	-0.009	0.082	0.039
M (V) 3	0.166	0.094	**0.931**	0.163	0.096	0.106	0.125	0.135	0.041	0.066	0.105	0.298	0.018	0.000	0.068	0.031	0.040	-0.029	0.093
M (P) 1	0.150	0.041	0.200	**1.000***	0.052	0.108	0.156	0.023	0.077	0.170	0.073	0.250	0.087	0.050	0.171	0.063	-0.036	0.039	0.115
ID 1	0.093	0.153	0.063	0.040	**0.659**	0.204	0.148	0.184	0.150	0.144	0.102	0.055	0.124	0.154	0.163	0.130	-0.080	-0.048	0.068
ID 2	0.030	0.122	0.106	0.084	**0.713**	0.102	0.105	0.096	0.109	0.093	0.193	0.172	0.156	0.065	0.100	0.184	0.043	0.041	0.118
ID 3	0.299	0.165	0.094	0.006	**0.814**	0.209	0.231	0.178	0.210	0.281	0.218	0.124	0.153	0.179	0.194	0.227	0.000	0.114	0.192
TCS 1	0.175	0.179	-0.005	0.011	0.206	**0.686**	0.180	0.161	0.372	0.356	0.217	0.019	0.280	0.147	0.217	0.275	-0.057	0.074	0.199
TCS 2	0.218	0.067	0.064	0.095	0.188	**0.828**	0.273	0.238	0.329	0.353	0.291	0.156	0.284	0.106	0.241	0.374	-0.030	0.140	0.338
TCS 3	0.094	0.109	0.191	0.139	0.129	**0.752**	0.315	0.297	0.274	0.428	0.193	0.178	0.283	0.021	0.146	0.224	-0.039	0.143	0.219
IS 1	0.195	0.123	0.100	0.106	0.167	0.247	**0.773**	0.348	0.200	0.391	0.538	0.211	0.207	0.184	0.315	0.224	0.033	0.120	0.325
IS 2	0.217	0.171	0.146	0.162	0.196	0.282	**0.797**	0.312	0.249	0.365	0.461	0.159	0.177	0.241	0.260	0.265	0.067	0.169	0.352
IS 3	0.129	0.223	0.111	0.120	0.226	0.123	**0.662**	0.309	0.263	0.266	0.334	0.190	0.214	0.165	0.219	0.107	-0.065	0.024	0.189
IS 4	0.012	0.185	0.036	0.050	0.085	0.281	**0.630**	0.275	0.339	0.264	0.324	0.117	0.277	0.078	0.160	0.172	-0.098	-0.005	0.245
MS 1	0.139	0.185	0.068	-0.078	0.100	0.168	0.366	**0.802**	0.255	0.317	0.298	0.094	0.318	0.278	0.302	0.198	0.209	0.168	0.371
MS 2	0.147	0.150	0.187	0.103	0.187	0.249	0.268	**0.705**	0.148	0.249	0.220	0.287	0.201	0.214	0.164	0.125	0.063	0.013	0.275
MS 3	0.178	-0.025	0.101	0.050	0.187	0.279	0.332	**0.767**	0.250	0.339	0.259	0.220	0.323	0.194	0.292	0.244	0.000	0.044	0.358
IDS 1	0.129	0.123	-0.006	0.114	0.054	0.276	0.260	0.212	**0.726**	0.274	0.251	0.071	0.384	0.155	0.233	0.244	0.083	0.041	0.275

IDS 2	0.115	0.082	0.085	0.056	0.255	0.409	0.295	0.271	**0.851**	0.358	0.302	0.021	0.405	0.179	0.331	0.300	-0.048	0.109	0.317
IDS 3	0.097	0.068	0.037	0.005	0.196	0.307	0.270	0.204	**0.774**	0.208	0.218	0.006	0.345	0.094	0.221	0.265	-0.121	0.067	0.183
PTCF 1	0.311	0.210	-0.008	0.067	0.200	0.356	0.306	0.274	0.337	**0.796**	0.439	0.142	0.268	0.233	0.273	0.306	0.059	0.125	0.397
PTCF 2	0.273	0.159	0.156	0.128	0.169	0.440	0.354	0.263	0.372	**0.813**	0.396	0.235	0.255	0.224	0.279	0.394	-0.089	0.087	0.322
PTCF 3	0.199	0.085	0.083	0.198	0.223	0.357	0.410	0.401	0.162	**0.747**	0.347	0.264	0.221	0.138	0.302	0.343	0.045	0.097	0.436
PIF 1	0.156	0.292	0.114	0.160	0.118	0.254	0.463	0.310	0.202	0.387	**0.747**	0.305	0.307	0.216	0.225	0.227	0.067	0.024	0.357
PIF 2	0.182	0.312	0.102	0.012	0.210	0.195	0.479	0.230	0.271	0.377	**0.826**	0.195	0.302	0.158	0.188	0.246	0.140	0.066	0.328
PIF 3	0.227	0.242	0.132	0.066	0.247	0.236	0.436	0.300	0.298	0.396	**0.748**	0.106	0.229	0.216	0.227	0.244	0.117	-0.013	0.262
PIF 4	0.150	0.117	0.026	-0.030	0.179	0.283	0.403	0.199	0.237	0.353	**0.693**	0.234	0.182	0.076	0.175	0.118	0.111	0.175	0.294
PMF 1	0.157	-0.011	0.285	0.207	0.095	0.126	0.139	0.154	0.078	0.253	0.249	**0.731**	0.140	0.085	0.133	0.188	-0.023	0.044	0.123
PMF 2	0.066	0.070	0.314	0.155	0.175	0.218	0.190	0.242	0.036	0.215	0.213	**0.820**	0.198	0.150	0.160	0.167	0.048	0.084	0.174
PMF 3	0.131	0.018	0.273	0.138	0.068	0.065	0.166	0.086	-0.087	0.147	0.158	**0.733**	0.113	0.039	0.031	0.079	-0.048	0.025	0.073
PMF 4	0.095	0.029	0.151	0.233	0.128	0.008	0.198	0.214	0.041	0.170	0.190	**0.681**	0.165	0.076	0.031	0.103	-0.012	-0.004	0.170
PIDF 1	0.028	0.136	0.017	0.065	0.076	0.189	0.193	0.317	0.410	0.240	0.195	0.160	**0.780**	0.155	0.225	0.216	0.017	0.104	0.217
PIDF 2	0.129	0.205	0.077	0.039	0.155	0.301	0.281	0.343	0.318	0.293	0.325	0.201	**0.855**	0.131	0.342	0.290	0.050	0.035	0.307
PIDF 3	0.118	0.205	-0.024	0.104	0.221	0.348	0.169	0.181	0.390	0.165	0.239	0.115	**0.605**	0.142	0.190	0.262	-0.117	-0.005	0.163
ATU 1	0.274	0.008	-0.033	0.037	0.126	0.104	0.174	0.263	0.155	0.246	0.185	0.096	0.167	**0.870**	0.401	0.302	0.066	0.101	0.439
ATU 2	0.243	0.114	-0.001	0.045	0.175	0.094	0.223	0.215	0.145	0.141	0.172	0.118	0.128	**0.719**	0.278	0.243	0.132	-0.038	0.280
FC 1	0.227	0.112	-0.070	0.126	0.091	0.192	0.160	0.169	0.214	0.262	0.185	0.129	0.186	0.335	**0.668**	0.279	0.045	0.056	0.380
FC 2	0.270	0.062	0.104	0.184	0.186	0.200	0.288	0.294	0.302	0.255	0.176	0.078	0.267	0.394	**0.854**	0.305	0.101	0.137	0.494
FC 3	0.233	0.121	0.141	0.041	0.174	0.205	0.286	0.282	0.211	0.285	0.239	0.100	0.306	0.189	**0.629**	0.218	0.050	0.038	0.370
U (De) 1	0.010	0.055	0.029	0.029	0.066	0.345	0.160	0.109	0.261	0.255	0.089	0.182	0.201	0.139	0.192	**0.678**	0.229	0.010	0.163
U (De) 2	0.250	0.112	0.078	0.066	0.187	0.334	0.199	0.262	0.185	0.398	0.301	0.224	0.272	0.306	0.295	**0.751**	0.182	0.016	0.480
U(De) 3	0.100	0.057	-0.046	0.038	0.290	0.194	0.254	0.174	0.315	0.299	0.198	0.015	0.264	0.286	0.313	**0.747**	0.140	0.053	0.331
U (Du) 1	0.098	0.112	0.025	-0.036	-0.005	-0.053	-0.001	0.121	-0.033	0.008	0.143	-0.001	-0.012	0.116	0.095	-0.053	**1.000***	0.203	0.102
U (F) 1	0.185	-0.050	0.005	0.039	0.073	0.159	0.127	0.106	0.095	0.131	0.080	0.058	0.058	0.054	0.114	0.159	0.113	**1.000***	0.059
UP 2	0.224	0.101	0.061	0.163	0.162	0.300	0.346	0.324	0.322	0.376	0.315	0.169	0.224	0.266	0.403	0.300	0.165	0.072	**0.775**

UP 4	0.387	0.158	0.117	0.080	0.150	0.227	0.323	0.380	0.242	0.443	0.312	0.153	0.213	0.437	0.589	0.227	0.780	0.062	**0.762**
UP 6	0.221	0.014	0.079	0.024	0.123	0.305	0.269	0.359	0.285	0.312	0.318	0.146	0.228	0.328	0.338	0.305	0.855	0.034	**0.778**
UP 7	0.169	0.073	-0.008	0.093	0.152	0.269	0.318	0.328	0.217	0.393	0.351	0.134	0.315	0.389	0.438	0.269	0.605	0.014	**0.819**

TC = Time Criticality, I = Interdependence, M (V) = Mobility (Variety), M (P) = Mobility (Proximity), ID = Information Dependency, TCS = Time Criticality Support, IS = Interdependence Support, MS = Mobility Support (MS), IDS = Information Dependency Support (IDS), U (F) = Use (Frequency), U (Du) = Use (Duration) U (De) = Use (Dependence), FC = Facilitating Conditions, ATU = Affect Toward Using, UP = User Performance

Table G.10. Fornell-Larker Criterion Results

	TC	I	M	M2	ID	TCS	IS	MS	IDS	PTCF	PIF	PMF	PIDF	FC	ATU	U (F)	U (Du)	U (De)	UP
TC	0.763	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0.274	0.814	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M (V)	0.150	0.041	0.803	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M (P)	0.164	0.116	0.197	SIC*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	0.220	0.199	0.052	0.122	0.732	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TCS	0.225	0.145	0.108	0.103	0.231	0.757	0	0	0	0	0	0	0	0	0	0	0	0	0
IS	0.207	0.231	0.156	0.140	0.230	0.337	0.719	0	0	0	0	0	0	0	0	0	0	0	0
MS	0.204	0.128	0.023	0.145	0.204	0.302	0.429	0.759	0	0	0	0	0	0	0	0	0	0	0
IDS	0.145	0.117	0.077	0.053	0.218	0.427	0.351	0.295	0.785	0	0	0	0	0	0	0	0	0	0
PTCF	0.331	0.191	0.170	0.096	0.253	0.489	0.457	0.402	0.365	0.786	0	0	0	0	0	0	0	0	0
PIF	0.235	0.326	0.073	0.126	0.246	0.317	0.591	0.344	0.332	0.500	0.755	0	0	0	0	0	0	0	0
PMF	0.145	0.039	0.250	0.347	0.167	0.159	0.232	0.251	0.042	0.274	0.281	0.743	0	0	0	0	0	0	0
PIDF	0.125	0.243	0.087	0.038	0.198	0.369	0.292	0.379	0.484	0.315	0.343	0.215	0.754	0	0	0	0	0	0
FC	0.337	0.130	0.171	0.082	0.209	0.272	0.338	0.343	0.340	0.364	0.270	0.137	0.345	0.724	0	0	0	0	0
ATU	0.324	0.065	0.050	-0.024	0.182	0.124	0.241	0.301	0.187	0.250	0.222	0.130	0.186	0.433	0.798	0	0	0	0
U (F)	0.185	-0.050	0.039	0.003	0.073	0.159	0.127	0.106	0.095	0.131	0.080	0.057	0.058	0.114	0.053	SIC*	0	0	0
U (Du)	0.098	0.112	-0.036	0.026	-0.005	-0.053	-0.001	0.122	-0.033	0.008	0.143	-0.001	-0.012	0.095	0.116	0.203	SIC*	0	0
U (De)	0.177	0.105	0.063	0.030	0.256	0.397	0.283	0.257	0.345	0.443	0.280	0.194	0.341	0.372	0.343	0.037	-0.073	0.727	0
UP	0.328	0.115	0.115	0.083	0.188	0.348	0.402	0.446	0.339	0.491	0.413	0.193	0.312	0.574	0.458	0.059	0.107	0.459	0.785

* SIC = Single Item Construct. Shaded diagonal cells represent square roots of construct AVE values.

TC = Time Criticality, I = Interdependence, M (V) = Mobility (Variety), M (P) = Mobility (Proximity), ID = Information Dependency, TCS = Time Criticality Support, IS = Interdependence Support, MS = Mobility Support (MS), IDS = Information Dependency Support (IDS), U (F) = Use (Frequency), U (Du) = Use (Duration) U (De) = Use (Dependence), FC = Facilitating Conditions, ATU = Affect Toward Using, UP = User Performance

Besides cross-loadings (Chin, 1998) and the Fornell-Larcker criterion (Fornell and Larcker, 1981), the Heterotrait-Monotrait ratio of correlations (HTMT), can be used to establish the discriminant validity of construct measures (Henseler, Ringle and Sarstedt, 2015, p. 116). First, monotrait-heteromethod correlations quantify relationships between two measurements of the same construct using different methods. Second, heterotrait-heteromethod correlations quantify relationships between two measurements of different constructs using different methods (Henseler et al., 2015, p. 120).

The HTMT ratio (Hair et al., 2015) is the average of heterotrait-heteromethod correlations (i.e. of indicators across constructs measuring different phenomena) relative to the average of monotrait-heteromethod correlations (i.e. of indicators within the same construct). If the indicators of two constructs exhibit a HTMT value less than 1, the true correlation between the two constructs is most likely different form one, and the constructs should differ (p. 121).

The HTMT ratio can be used to establish discriminant validity by comparing it to a predefined threshold. If the HTMT value exceeds this threshold, then it can be concluded that there is a lack of discriminant validity (Henseler et al., 2015). Gold, Malhotra and Segars (1990) suggested that for discriminant validity to be established, the estimated correlation between all construct pairs should be below the threshold of 0.90 (Gold, Malhotra and Segars, 2001), notated as $HTMT_{.90}$. However, the alternative threshold of 0.85 (Clark and Watson, 1995), notated as $HTMT_{.85}$, is also deemed acceptable. Construct HTMT results are shown in Table G.11.

Table G.11. HTMT$_{.90}$ Results																			
	ATU	FC	I	ID	IDS	IS	M (V)	M (P)	MS	PIDF	PIF	PMF	PTCF	TC	TCS	U (De)	U (Du)	Use (F)	UP
ATU																			
FC	0.858																		
I	0.173	0.272																	
ID	0.378	0.409	0.375																
IDS	0.330	0.544	0.211	0.324															
IS	0.428	0.543	0.411	0.349	0.519														
M (V)	0.077	0.222	0.060	0.076	0.089	0.180													
M (P)	0.106	0.220	0.252	0.175	0.082	0.200	0.251												
MS	0.564	0.571	0.303	0.343	0.426	0.637	0.127	0.223											
PIDF	0.362	0.599	0.452	0.334	0.765	0.452	0.118	0.085	0.584										
PIF	0.384	0.442	0.529	0.352	0.460	0.789	0.103	0.169	0.493	0.493									
PMF	0.211	0.224	0.100	0.228	0.134	0.323	0.286	0.464	0.369	0.301	0.363								
PTCF	0.441	0.610	0.345	0.364	0.524	0.634	0.201	0.184	0.591	0.479	0.700	0.365							
TC	0.577	0.522	0.514	0.312	0.198	0.269	0.163	0.256	0.285	0.196	0.337	0.215	0.455						
TCS	0.230	0.462	0.263	0.374	0.633	0.488	0.134	0.172	0.479	0.597	0.449	0.237	0.750	0.306					
U (De)	0.670	0.673	0.203	0.413	0.561	0.423	0.082	0.092	0.404	0.583	0.414	0.291	0.705	0.296	0.650				
U (Du)	0.186	0.125	0.163	0.073	0.129	0.109	0.036	0.026	0.149	0.105	0.167	0.051	0.099	0.108	0.069	0.098			
U (F)	0.130	0.146	0.066	0.120	0.111	0.131	0.039	0.060	0.123	0.082	0.106	0.061	0.158	0.188	0.195	0.048	0.203		
UP	0.745	0.863	0.196	0.248	0.449	0.510	0.129	0.100	0.615	0.439	0.533	0.237	0.651	0.401	0.471	0.661	0.144	0.065	

TC = Time Criticality, I = Interdependence, M (V) = Mobility (Variety), M (P) = Mobility (Proximity), ID = Information Dependency, TCS = Time Criticality Support, IS = Interdependence Support, MS = Mobility Support (MS), IDS = Information Dependency Support (IDS), U (F) = Use (Frequency), U (Du) = Use (Duration) U (De) = Use (Dependence), FC = Facilitating Conditions, ATU = Affect Toward Using, UP = User Performance

Appendix H Analysis of Covariance (ANCOVA)

Analysis of Covariance (ANCOVA) is a statistical procedure used to examine the influence of one or more factors on a dependent variable, whilst partialling out or removing the effects of one or more covariates (Brace et al., 2012, p. 295). It is informed by the following assumptions:

1. The covariate(s) should not differ across groups in the experiment.
2. The relationship between the dependent variable and the covariate(s) should be similar for groups.

To test assumption 1, Analysis of Variance (ANOVA), was conducted with age, gender, experience as a CHW, education level, and tool use experience, by user groups (Table H.1). Relationships involving age (p = 0.000) and experience as a CHW (p = 0.002), were significant. Consequently, age and experience as a CHW were excluded from the ANCOVA.

Table H.1. ANOVA: User Group on Covariate(s)

Variable		**Sig (p)**
Independent	Dependent	
User Group	Age	0.000***
	Gender	0.703
	Experience as a CHW	0.002**
	Education Level	0.591
	Tool Use Experience	0.574

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

To test assumption 2, ANOVA was conducted with user group as the independent variable and each of the eleven CHW Reporting Performance (CHWRP) indicators (1-11) as outcomes. Interactions between user group and each of the three remaining covariates i.e. gender, education level, and use experience, were included. ANOVA results for the interaction between user group and gender are shown in Table H.2.

Table H.2. ANOVA: User Group and Gender		
Interaction Term	**Dependent Variable (CHWRP)**	**Sig (p)**
User Group * Gender	1	0.321
	2	0.597
	3	0.242
	4	0.353
	5	0.045*
	6	0.123
	7	0.640
	8	0.082
	9	0.309
	10	0.984
	11	0.013*

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

The interaction of user group and gender was significant where CHWRP 1 (monthly households visited) and CHWRP 2 (percentage of monthly household visits reported) were the dependent variables. Consequently, gender was excluded from ANCOVA where CHWRP 1 (monthly households visited) and CHWRP 2 (percentage of monthly household visits reported) were dependent variables. ANOVA results, including the eleven CHWRP indicators and the interaction, are shown in Table H.3.

Table H.3. ANOVA: User Group and Education Level		
Interaction Term	**Dependent Variable (CHWRP)**	**Sig (p)**
User Group * Education Level	1	0.157
	2	0.009**
	3	0.876
	4	0.122
	5	0.524
	6	0.126
	7	0.370
	8	0.161
	9	0.069
	10	0.069
	11	0.290

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

The interaction of user group and education level was significant where CHWRP 2 (percentage of monthly household visits reported) was the dependent variable. Consequently, education level was excluded from ANCOVA where CHWRP 2 (percentage of monthly household visits reported) was a dependent variable. ANOVA results including the eleven CHWRP indicators and the interaction of user group and use experience are shown in Table H.4.

Table H.4.ANOVA: User Group and Use Experience

Interaction Term	**Dependent Variable (CHWRP)**	**Sig (p)**
User Group * Tool Use Experience	1	0.069
	2	0.048*
	3	0.502
	4	0.212
	5	0.160
	6	0.340
	7	0.301
	8	0.400
	9	0.286
	10	0.824
	11	0.074

******* $p < 0.0001$, ****** $p < 0.01$, ***** $p < 0.05$

The interaction of user group and experience was significant for relationships where CHWRP 2 (percentage of monthly household visits reported) was the dependent variable. Consequently, use experience would be excluded from ANCOVA where OUP 2 (percentage of monthly household visits reported) was a dependent variable. Where interaction terms were significant, Assumption 2 (homogeneity of regression slopes) was violated. Following testing of Assumptions 1 and 2 using ANOVA, ANCOVA was conducted. Gender, education level, and use experience, were selectively controlled for in the ANCOVA.

Table H.5. ANCOVA: Controls			
Control Variable			**Dependent Variable (CHWRP)**
Gender	Education Level	Use Experience	
✓	✓	✓	1
✓	X	X	2
✓	✓	✓	3
✓	✓	✓	4
X	✓	✓	5
X	✓	✓	6
✓	✓	✓	7
✓	✓	✓	8
✓	✓	✓	9
✓	✓	✓	10
X	✓	✓	11

Appendix I Sequential (Hierarchical) Regression

Sequential (Hierarchical) Regression is an inferential statistical procedure that involves the inclusion of predictors in a sequence determined by theoretical or empirical considerations (Brace et al., 2012). It is used to investigate linear relationships between multiple variables, whilst controlling for the effects of covariates (p. 270). Following Sequential Regression, the variate was examined to ensure that the following assumptions were met:

1. Linearity: The relationship between the independent and dependent variable should be linear.
2. Homoscedasticity: The variance of errors should be the same for all levels of the independent variable.
3. Independence: For observations, errors should be independent such that they are uncorrelated.
4. Normality: The errors should be normally distributed, approximating a normal curve.
5. Multicollinearity: The independent variables should not correlate at high levels.

To test assumptions 1, 2, and 4, the residual of the eleven CHWRP indicators was examined. Scatterplots of the residual for each of these indicators were examined. The residual examined showed clusters around the middle of the scatterplots, forming a rectangular shape (Brace et al., 2012). The scatterplots showed linear relationships between the residual and predicted value (Osborne and Waters, 2002). Therefore the assumptions 1 (Linearity), and 2 (Homoscedasticity), were satisfied. To test assumption 3 (Independence), the auto-correlation of residuals, was examined using Durbin-Watson values.

Table I.1. Durbin-Watson Test							
Predictors						**Criterion Variable (CHWRP)**	**Durbin-Watson Statistic**
1_b					**2_b**		
Age	Gender	Experience as a CHW	Education Level	Use Experience	User Group		
✓	✓	✓	✓	✓	✓	1	1.330
✓	✓	✓	✓	✓	✓	2	1.602
✓	✓	✓	✓	✓	✓	3	1.699
✓	✓	✓	✓	✓	✓	4	1.561
✓	✓	✓	✓	✓	✓	5	1.977
✓	✓	✓	✓	✓	✓	6	1.676
✓	✓	✓	✓	✓	✓	7	1.713
✓	✓	✓	✓	✓	✓	8	1.880
✓	✓	✓	✓	✓	✓	9	1.618
✓	✓	✓	✓	✓	✓	10	1.817
✓	✓	✓	✓	✓	✓	11	1.753

1_b = First Block: Covariates in Regression Model, 2_b = Second Block: Independent Variable

The Durbin-Watson test statistic can vary between values of 0 and 4. Since values 'less than 1 or greater than 3' (Field, 2009) were not found, Assumption 3 (Interdependence) was met. To test and satisfy assumption 4 (Normality), Probability Plots (P-Plots) of the residuals (Brace et al., 2012) were examined and these were found to be normally distributed (the residual data points observed formed approximately straight lines). To test assumption 5, Tolerance and Variance Inflation Factor (VIF) values were calculated. Due to high Tolerance and low VIF values (Brace et al., 2012), Assumption 5 (Multicollinearity) was not violated.

Table I.2. Multicollinearity Test						
Tolerance Value and (VIF) Values						**Dependent Variable (CHWRP)**
Age	Gender	Experience as a CHW	Education Level	Use Experience	User Group	
0.926 (1.080)	0.991 (1.009)	0.935 (1.070)	0.992 (1.008)	0.986 (1.014)	0.928 (1.078)	1
0.911 (1.098)	0.992 (1.008)	0.918 (1.089)	0.988 (1.012)	0.988 (1.012)	0.927 (1.078)	2
0.925 (1.081)	0.990 (1.011)	0.960 (1.041)	0.988 (1.012)	0.978 (1.1023)	0.945 (1.058)	3
0.916 (1.092)	0.990 (1.011)	0.948 (1.054)	0.991 (1.009)	0.983 (1.017)	0.935 (1.069)	4
0.913 (1.095)	0.985 (1.015)	0.955 (1.047)	0.991 (1.009)	0.970 (1.031)	0.928 (1.077)	5
0.928 (1.078)	0.989 (1.012)	0.953 (1.049)	0.990 (1.010)	0.972 (1.029)	0.923 (1.083)	6
0.924 (1.082)	0.994 (1.006)	0.954 (1.049)	0.990 (1.010)	0.967 (1.034)	0.918 (1.089)	7
0.915 (1.093)	0.993 (1.007)	0.946 (1.057)	0.993 (1.007)	0.969 (1.032)	0.911 (1.098)	8
0.925 (1.081)	0.992 (1.008)	0.933 (1.071)	0.991 (1.009)	0.988 (1.012)	0.927 (1.078)	9
0.925 (1.081)	0.992 (1.008)	0.933 (1.071)	0.991 (1.009)	0.988 (1.012)	0.927 (1.078)	10
0.922 (1.085)	0.994 (1.006)	0.936 (1.069)	0.995 (1.005)	0.988 (1.012)	0.912 (1.096)	11

Appendix J Structural Equation Modelling (SEM)

The multi-variate method of Partial Least Squares – Structural Equation Modelling (PLS – SEM) is a second-generation technique (Hair et al., 2014). Second-generation techniques enable researchers to incorporate unobservable variables indirectly observed by indicator variables (p. 2).

J.1 Path Models with Latent Variables

Path models are diagrams used to visualize hypotheses and variable relationships examined using SEM (Hair, Ringle and Sarstedt, 2011). Path models comprise constructs or latent variables (not directly measured), and their indicator items, or manifest variables (directly measured). Relationships between these constructs and their indicators are depicted using arrows (Hair et al., 2014). In path models, there are exogenous (predictor), and endogenous (criterion) variables. The former are used to explain other constructs in the path model. The latter represent those constructs that are being explained in the path model. Path models are developed based on theory, a set of systematically related propositions developed following scientific methods used to explain and predict outcomes (p. 12).

J.2 Approaches

There are two approaches to SEM, namely Partial Least Squares (PLS) and Covariance-Based (CB). The use of either approach is based on their distinguishing features (Hair et al., 2012). PLS-SEM is preferred if the objective of SEM is to predict and explain target constructs. Compared to the CB approach, which is a Maximum Likelihood (ML) procedure, PLS-SEM is an Ordinary Least Squares (OLS) regression-based method (Hair et al., 2014, p. 14). There are four components instructive to the use of PLS-SEM (Hair, Ringle and Sarstedt, 2011; Hair et al., 2012a; Hair et al., 2012b; Ringle, Sarstedt and Straub, 2012):

1. The data.
2. Model properties.
3. The PLS-SEM algorithm.
4. Model evaluation issues.

PLS-SEM works efficiently with complex models and is a non-parametric procedure (not based on data distribution assumptions). Moreover, PLS-SEM can easily accommodate reflective and formative measurement models, and single-item constructs without identification problems. By applying PLS-SEM, researchers benefit from high parameter estimation efficiency. Furthermore, PLS-SEM has greater statistical power than CB-SEM (Hair et al., 2014, p. 15).

Findings reported in prior studies have indicated that the differences between PLS-SEM and CB-SEM are minor. As such, PLS-SEM and CB-SEM results do not differ significantly (Reinartz, Haenlein and Henseler, 2009). Therefore, when selecting a suitable analysis procedure for SEM, researchers can consider either approach. Most importantly, researchers ought to use the SEM procedure most suited to their research objectives, data attributes, and model setup (Roldan and Sanchez Franco, 2012). The key characteristics of PLS-SEM are summarized in Table J.1.

Table J.1. Key Characteristics of Partial Least Squares – Structural Equation Modeling (PLS – SEM)	
Data Characteristics	
Sample Sizes	• No identification issues with sample sizes. • Generally achieves high levels of statistical power with small sample sizes. • The precision (consistency) of PLS-SEM estimations increase with larger sample sizes.
Distribution	PLS-SEM is a non-parametric technique (no distributional assumptions).
Missing Values	Highly robust as long as missing values do not exceed a reasonable level.
Scale of Measurement	Functional with metric data, quasi-metric (ordinal) scaled data, and binary coded variables (with certain restrictions). Is somewhat limited when using categorical data to measure endogenous latent variables.
Model Characteristics	
Number of Items in Each Construct Measurement Model.	Handles construct measures with single and multi-item measures.
Relationships between Constructs and their Indicators	Easily incorporates reflective and formative measurement models.
Model Complexity	Handles complex model with multiple structural model relations. Larger numbers of indicators usefully contribute to reducing PLS-SEM bias.
Model Setup	No causal loops allowed in the structural model (exclusive to recursive models).
PLS-SEM Algorithm Properties	
Objective	Minimizes the amount of unexplained variance (maximizes R^2 values).
Efficiency	Converges after a few iterations (even with complex models and/or large

	sets of data) to the optimum solution; efficient algorithm.
Construct Scores	Estimated as linear combinations of their indicators. Used for predictive purposes. Can be used as input for subsequent analyses. Not affected by data inadequacies.
Parameter Estimates	Structural model relationships are somewhat underestimated (PLS-SEM bias). Measurement model relationships are somewhat overestimated (PLS-SEM bias). Consistency at large. High statistical power levels.
Model Evaluation Issues	
Evaluation of the Overall Model	No global goodness-of-fit criterion.
Evaluation of Measurement Models	Reliability and Validity assessments using multiple criteria.
Evaluation of the Structural Model	Collinearity among constructs, significance of path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2 and q^2 effect size)
Additional Analysis	Impact-performance matrix analysis, mediating effects, hierarchical component models, multi-group analysis, uncovering and treating unobserved heterogeneity, measurement model invariance, moderating effects.

Notably, PLS-SEM is not without its limitations. For instance, the technique cannot be applied when there are causal loops in structural models, or circular relationships between latent variables (non-recursive model). Regarding bias and consistency, PLS-SEM parameter estimates are not always optimal (Hair et al., 2014, p. 18).

J.3 Model Specification

Structural models are used to describe the relationships between latent variables (constructs). Measurement models represent relationships between these constructs and their indicators (Hair et al., 2014). These relationships are determined based on measurement theory. Sound theory is instrumental to obtaining useful PLS-SEM results (p. 41).

To develop constructs, researchers must consider typologies representing reflective and formative measurement models. The reflective measurement (Mode A) model is based on classical test theory, based on the premise that measures represent effects (manifestations) of an underlying construct. Consequently, causality emanates from the construct to its indicators (p. 42). Conversely, the formative measurement (Mode B) model is based on the assumption that indicators cause the construct (p. 43).

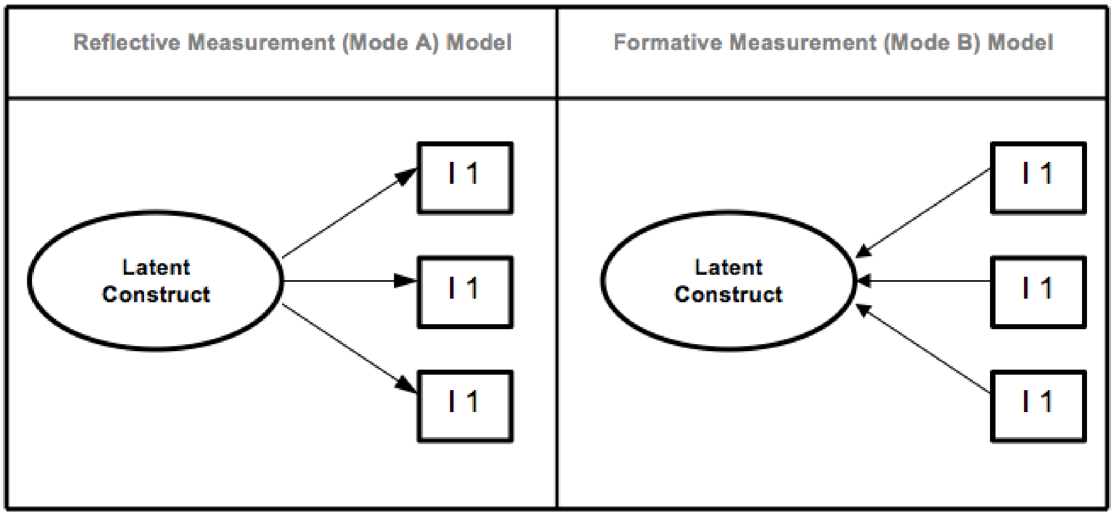

Figure J.1. Measurement Model Types

The specification of the content of constructs, determines the measurement model type[97] used. There are a number of guidelines[98] that are useful for measurement model selection:

Table J.2. Guidelines: Measurement Model		
Criterion	Decision	Reference
Causal priority between indicator and construct	• If from construct to indicator, model is reflective. • If from indicators to construct, model is formative.	Diamantopoulos and Winklhofer (2001)
Is the construct a trait that explains indicators rather than their combination?	• If yes, model is reflective. • If no, model is formative.	Fornell and Bookstein (1982)
Do the indicators represent consequences or causes of the construct?	• If yes, model is reflective. • If no, model is formative.	Rossiter (2002)
If the assessment of the trait is altered, all indicators will change similarly (assuming they are coded equally)?	• If yes, model is reflective. • If no, model is formative.	Chin (1998)
Are the items mutually interchangeable?	• If yes, model is reflective. • If no, model is formative.	Jarvis, MacKenzie, and Podsakoff (2003)

[97] The type of measurement model is determined by construct conceptualization and the aim of the study.

[98] A data-driven approach must be supplemented with theoretical considerations consistent with the above guidelines (Hair et al., 2014, p. 46).

Appendix K Bootstrapping

K.1 Procedure

The PLS-SEM approach is based on the assumption that data are not normally distributed. Consequently, a non-parametric, bootstrap procedure (Efron and Tibshirani, 1986; Davison and Hinkley, 1997) must be used to test path coefficient significance. Bootstrapping involves drawing a large number of subsamples (i.e. bootstrap samples), from an original sample with replacement (Hair et al., 2014). In other words, each time an observation is randomly drawn from a sample population, it is returned before a subsequent observation (i.e. the population from with the observation is drawn always contains all the same elements). Therefore, for a particular subsample, an observation can be selected either more than once, or never (p. 131). The number of bootstrap samples drawn should be large, but at least be equal to the number of valid observations in the dataset. As a rule of thumb, 5000 bootstrap samples are recommended. In addition, the size of each bootstrap must be specified (Hair et al., 2014). The accepted guideline is that each bootstrap should equate the number of observations in the original sample. For example, if there are 100 valid observations in the original sample, then each of the 5000 bootstrap samples should have 100 cases. In this does not occur, then the results of significance testing will be systematically biased (p. 132). The bootstrap procedure is shown in Figure K.1.

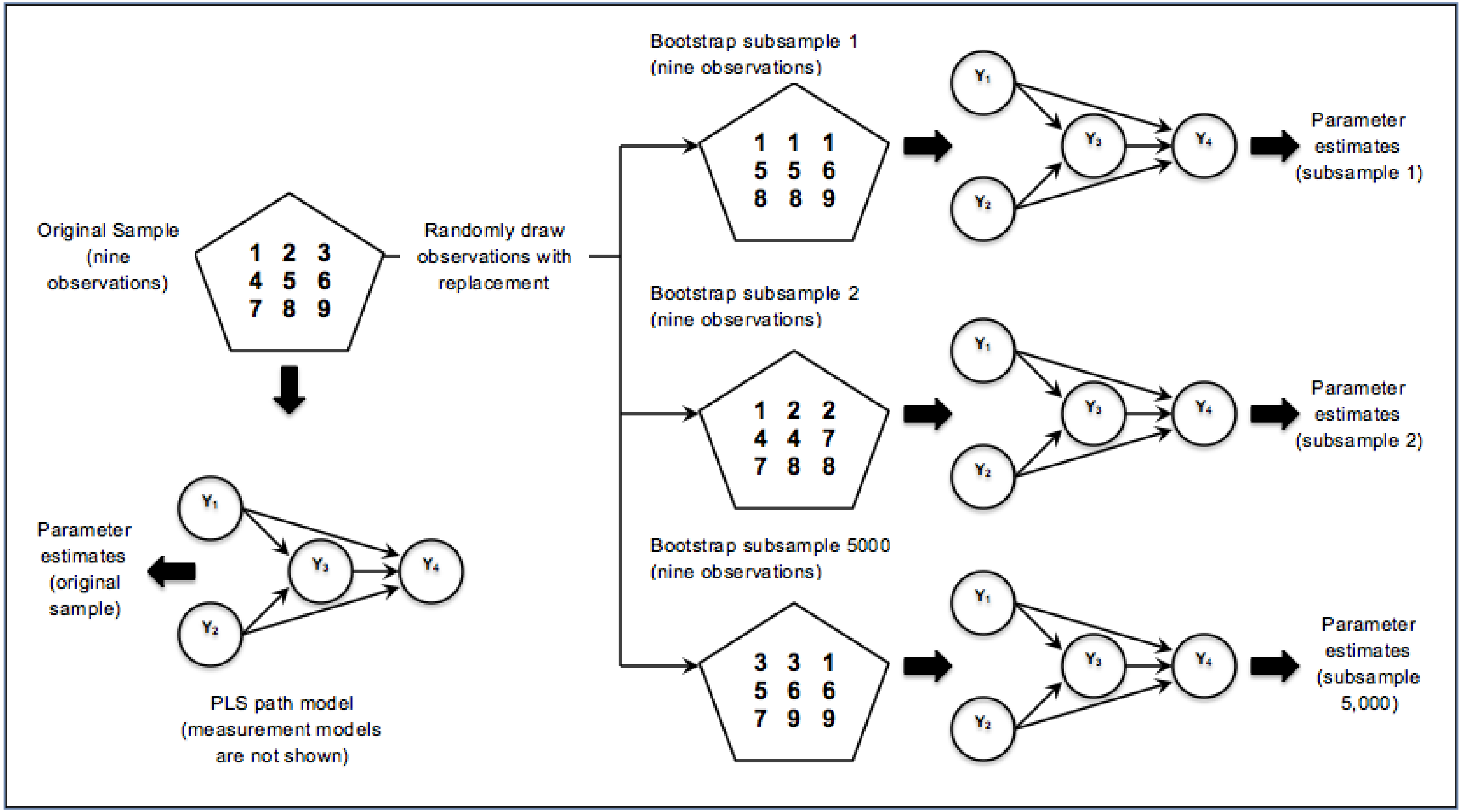

Figure K.1. Bootstrap Routine (Hair, Hult, Ringle and Sarstedt, 2014, p. 133)

The bootstrapping procedure follows a *t* distribution with degrees of freedom (*df*). The degrees of freedom (*df*) are the number of values in the final calculation of the test statistic that are free to vary, and equal to the number of observations minus 1 (Hair et al., 2014). The *t* distribution is well approximated by the normal (Gaussian) distribution for more than 30 observations. The number of observations usually exceeds this threshold such that the normal (Gaussian) quantiles can be used to determine critical *t* values for significance testing (Hair et al., 2014). For example, when the size of the resulting *t* value exceeds 1.96, the assumption is that the path coefficient is significantly different from zero at a significance level of 5% ($\propto$ = 0.05; two-tailed test). The *t* values for significance levels of 1% ($\propto$ = 0.01; two-tailed test), and 10% ($\propto$ = 0.10; two-tailed test), are 2.57 and 1.65 respectively (Hair et al., 2014, p. 134). In using PLS-SEM bootstrapping procedures, the signs of latent variable scores are indeterminate (Wold, 1985). This results in arbitrary sign changes in bootstrapped estimates of path coefficients, compared to those obtained from the original sample (Hair et al., 2014). This pulls the mean value of bootstrap results toward zero, inflating the corresponding bootstrap standard error (se^{*}_{w1}) upward, and decreasing the t value (p. 135). There are three approaches that can be followed to remedy sign changes.

First, the default, no sign change option involves accepting the negative impact of sign changes on the results for the empirical *t* value obtained. Second, the individual-level sign change option is used to reverse signs if an estimate for a bootstrap sample results in the opposite sign to that of the original sample. The signs in the measurement and structural models of each bootstrap sample are aligned with the signs in the original sample to avoid sign change problems. Third, the construct-level sign change option is used to test a group of path coefficients simultaneously and compare the signs of original PLS path model estimates with those of the bootstrap sub-sample (Hair et al., 2014, p. 135). If most of the signs need to be reversed through bootstrapping to match the signs of the model estimated using the original sample, all signs are reversed through bootstrapping, otherwise, no signs are changed. The construct-level sign change is a compromise between the no sign changes and individual-level changes options. Results obtained using the sign change options do not differ much, provided the original estimates are not close to zero. If, however, the original estimates are close to zero, then sign reversal may systematically reduce the bootstrapping standard error (se^{*}). The no sign change option results in the most conservative outcome. If path coefficients are significant under the no sign change option, they will also be significant when using the alternatives. Otherwise, the individual sign change option should be used since it yields the highest *t* values when comparing the three sign change options. If the result still is not significant, the path coefficient is not significant. However, if the result is not significant under the no sign change option but is significant under the individual-level sign change option, then the construct-level change option should be used to counter-balance the two (Hair et al., 2014, p. 135).

The interpretation procedure used to evaluate these sign change options is shown in Figure K.2.

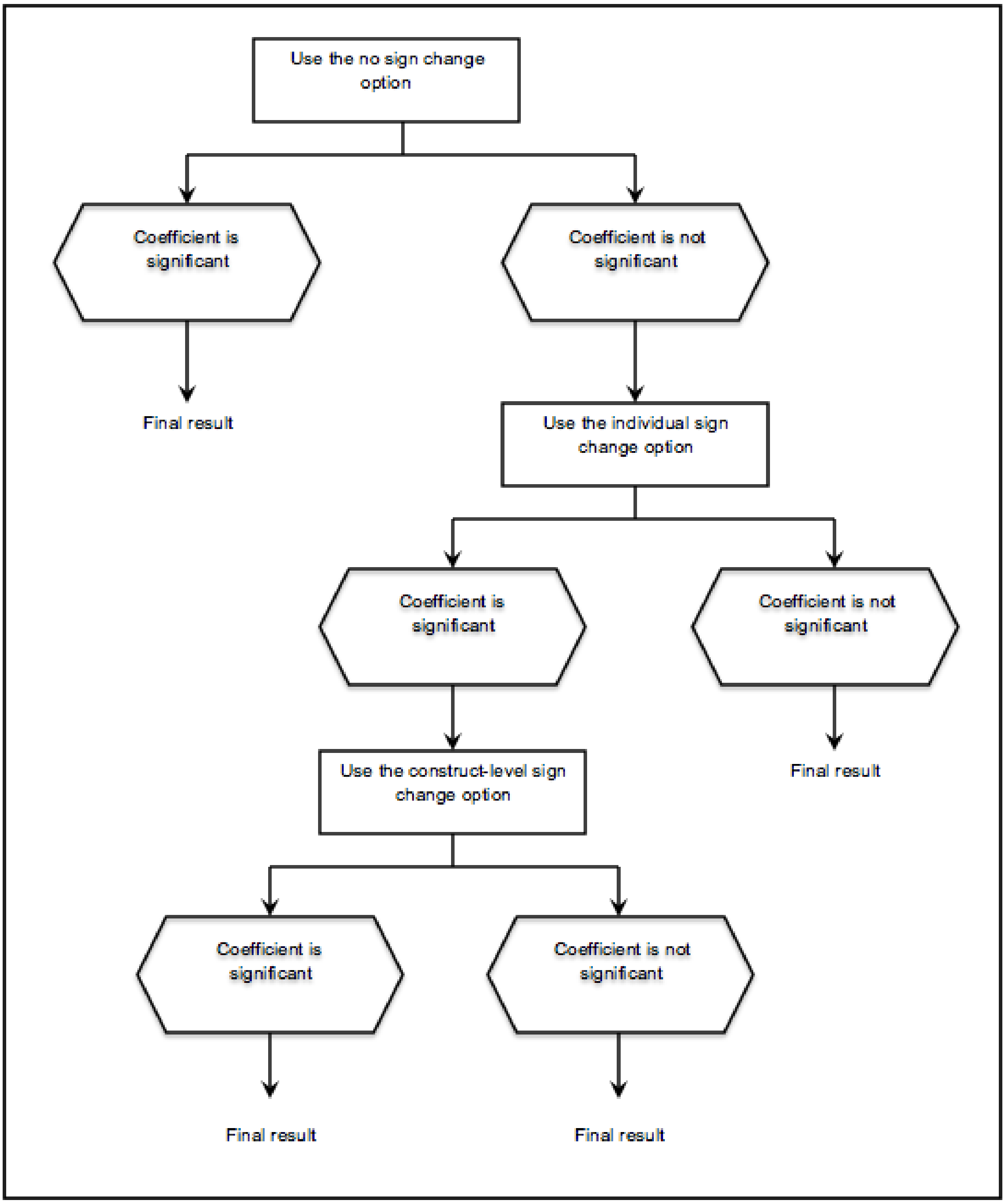

Figure K.2. Bootstrap Sign Change Options (Hair, Hult, Ringle and Sarstedt, 2014, p. 137)

Appendix L Task-Technology Fit (TTF) as Moderation

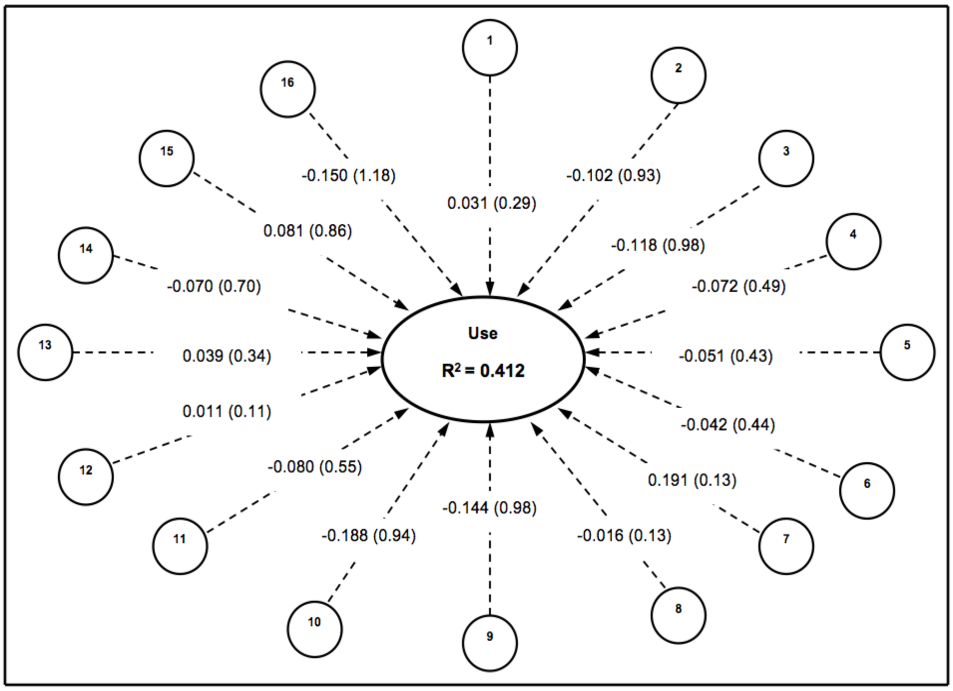

Figure L.1. Path Model: Task-Technology Fit (TTF) as Moderation (Interaction) Effects on Use

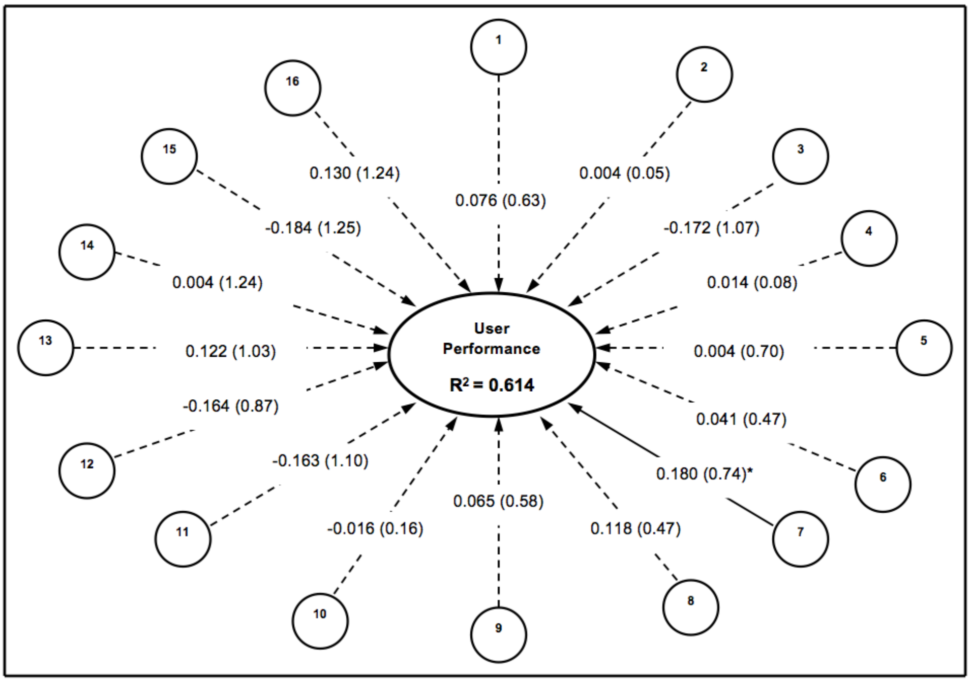

Figure L.2. Path Model: Task-Technology Fit (TTF) as Moderation (Interaction) Effects on User Performance

* p < 0.01, ***p < 0.05, ***p < 0.01.

1 = TC x TCS, **2** = TC x IS, **3** = TC x MS, **4** = TC x IDS, **5** = I x TCS, **6** = I x IS, **7** = I x MS **8** = I x IDS,
9 = M x TCS, **10** = M x IS, **11** = M x MS, **12** = M x IDS, **13** = ID x TCS, **14** = ID x IS, **15** = ID x MS, **16** = ID x IDS

Appendix M Response Surface Methodology

M.1 Polynomial Regression

A reflective first-order, formative second-order Type II structural path model (Figure M.1), was estimated[99], in order to obtain unstandardized latent variable scores[100] for Polynomial Regression.

Prior to response surface analysis, Polynomial Regression must be conducted first (Edwards, 1994). Polynomial Regression is based on three fundamental assumptions (Shanock, Baran, Gentry, Patison, and Heggestad, 2010).

First, the component measures must co-exist in the same conceptual domain (Shanock et al., 2010). For example, the task performed, and the technology used, conceptually co-exist. Since these two components influence use and user performance, a discrepancy (misfit) between the task (user needs), and the technology (tool functions), is plausible. Second, component measures must often be captured using equivalent scales (Edward, 2002). Scale equivalence is necessary to determine their degree of correspondence (p. 360). Third, component measures must be interval or ratio (Pedhazur, 1997). For instance, task and technology components were measured using a seven-point Likert scale from 1 = ‘strongly disagree’ to 7 = ‘strongly agree’.

Polynomial Regression (Edwards, 1993) and Response Surface Methodology (Edwards, 2002) are used to examine:

1. How the agreement (fit) between two variables, relates to an outcome.
2. How the degree of discrepancy (misfit) between two variables relates to an outcome.
3. How the direction of the discrepancy (misfit) between two variables, relates to an outcome.

[99] A bootstrapping procedure (5000 re-samples) was used.
[100] The unstandardized latent variable scores were imported into SPSS, and used to run Polynomial Regression analyses.

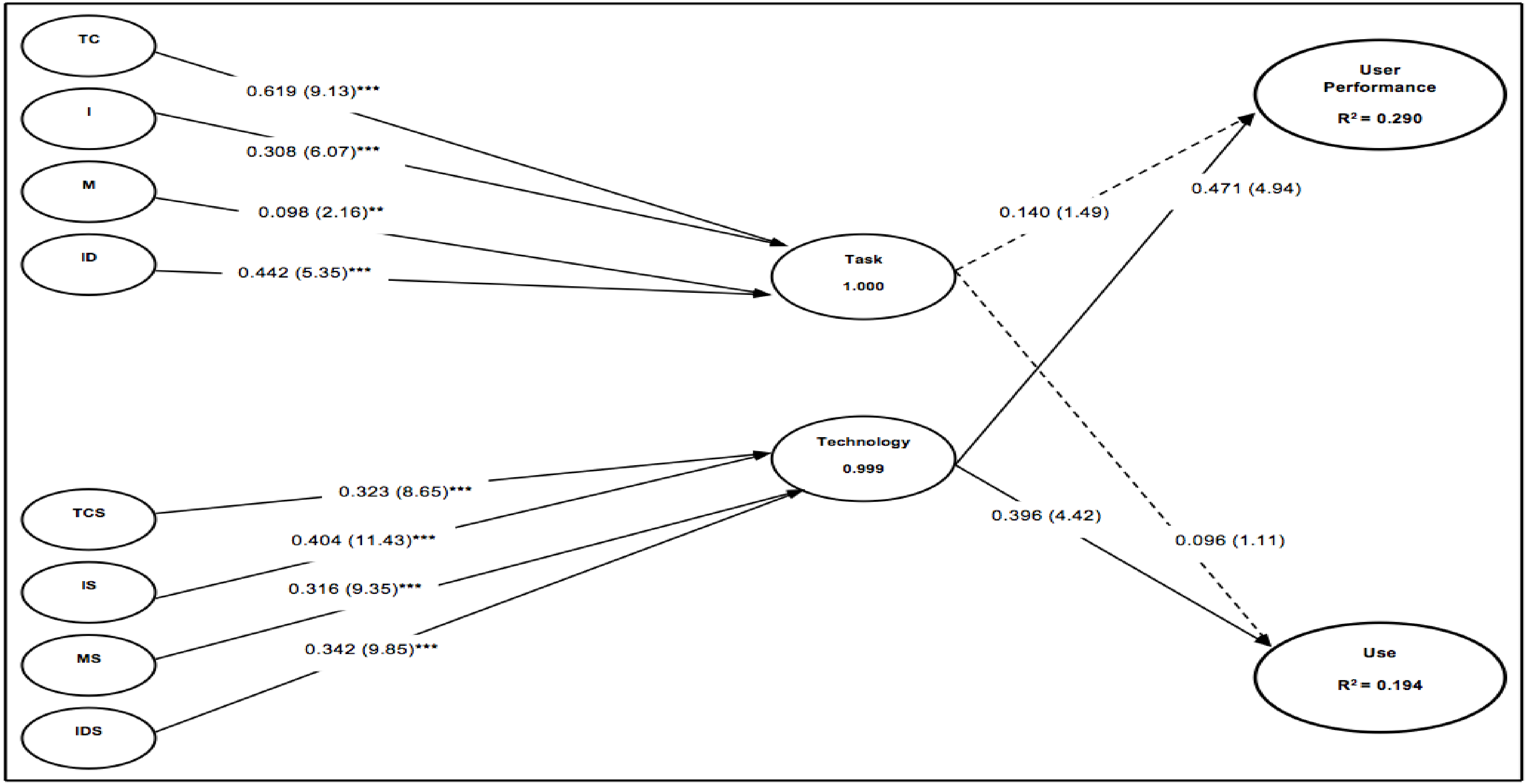

Figure M.1. Path Model – Task-Technology Fit (TTF): Reflective First-Order, Formative Second-Order Type II Model

* p < 0.01, ****p < 0.05. ***p < 0.01

M.2 Response Surface Features

Table M.1. Response Surface Features		
Feature	**Expression**	**Interpretation**
Stationary Point	$X_0 = \frac{b_2b_4 - 2b_1b_5}{b_3b_5 - b_4^2}$, $Y_0 = \frac{b_2b_4 - 2b_1b_5}{b_3b_5 - b_4^2}$	• This is the point at which the surface slope is zero in all directions. • For a concave surface, the stationary point represents the maximum. For a convex surface, it represents the minimum. For a saddle surface, it lies along the intersection of the lines along which upward and downward surface curvatures are greatest. • The stationary point is used to determine the response surface structure. For positive criteria (e.g. individual performance), it is used to identify the peak (dome) of the surface. For negative criteria (e.g. dissatisfaction), it is used to identify the trough (bowl) of the surface.
Principal Axes (1ST and 2nd)	1st principal axis: $Y = p_{10} + p_{11}X$ with $p_{11} = \frac{b_5 - b_3 + \sqrt{((b_3 - b_5)^2 + b_4^2}}{b_4}$ (slope) $p_{10} = Y_0 - p_{11} X_0$ (intercept) 2nd principal axis: $Y = p_{20} + p_{21}X$ with $p_{21} = \frac{b_5 - b_3 + \sqrt{((b_3 - b_5)^2 + b_4^2}}{b_4}$ (slope) $p_{20} = Y_0 - p_{11} X_0$ (intercept)	• The principal axes indicate the overall orientation of the surface, regarding the X, Y plane. These represent lines in the X, Y plane perpendicular to one another, intersecting the stationary point. • For a concave surface, the first principal axis is the line along which the downward surface curvature is minimized. The second principal axis is the line along which the downward surface curvature is maximized. • For a convex surface, the first principal axis is the line along which the upward surface curvature is maximized. The second principal axis is the line along which the upward surface curvature is minimized. • For a saddle surface, the first principal axis is the line along which the upward curvature of the surface is maximized. The second principal axis is the line along which the downward surface curvature is maximized.
Line of Congruence (Fit)	$Y = X$ with following shape along this line: $Z = b_0 + (b_1 + b_2)X + (b_3 + b_4 + b_5)X^2 + e$ where $ax = b_1 + b_2$ (slope at X = 0, Y = 0) $ax_2 = b_3 + b_4 + b_5$ (curvature)	• The surface shape along the line of perfect congruence. • The examination of this line involves testing its slope and curvature. If *ax* (its slope at the origin), significantly differs from zero, and is positive (or negative), and ax_2 does not (i.e. no significant curvature), the surface slope if positive (negative) linear, indicating that when the two predictors are congruent (fit) the criterion (outcome) increases (decreases) as their values increase.
Line of Incongruence (Mis-Fit)	$Y = -X$ with following shape along this line: $Z = b_0 + (b_1 + b_2)X + (b_3 - b_4 + b_5)X^2 + e$ where $ax = b_1 - b_2$ (slope at X = 0, Y = 0) $ax_2 = b_3 - b_4 + b_5$ (curvature)	• Definition: The shape of the surface along the line of incongruence. • The examination of this line involves testing its slope and curvature. If *ax* does not significantly differ from zero ($ax = 0$) and ax_2 is negative and does ($ax<0$), the response surface will have an inverted *U-shape* (i.e., curved upward) along the $Y = -X$ line, with its peak at $Y = X$. If *ax* significantly differs from zero and is positive (or negative) and a_2 does not ($ax_2 = 0$), the surface slope along the line of incongruence is linear indicating that the outcome variable increases

		(decreases) along the line of incongruence.
Lateral Shift and Rotation	$\frac{b_3 - b_4}{2(b_3 - b_4 + b_5)}$	• The magnitude and direction of the lateral shift along the $Y = X$ line is also expressed using the formula in the left column. A positive value represents a shift toward the region where $Y > X$. A negative value represents a shift toward the region where $Y < X$. • The examination of this shift helps determine what type of incongruence (i.e., $Y > X$ or $Y < X$), has more or less impact on the outcome variable. • The magnitude and direction of the surface rotation can also be analysed by looking at b_3, b_4, and b_5. If b_3 and b_5 are equal, then the surface does not rotate, independent of b_4. If b_3 is less than b_5, the surface rotates clockwise, otherwise it rotates counter-clockwise. In both cases, the magnitude of the rotation is determined not only by the difference of b_3 and b_5, but also by b_4, with larger rotations for smaller values of b_4.

Appendix N Task-Technology Fit (TTF) as Mediation

Task-Technology Fit (TTF) as Mediation, is based on the generic mediator model[101] shown in Figure N.1.

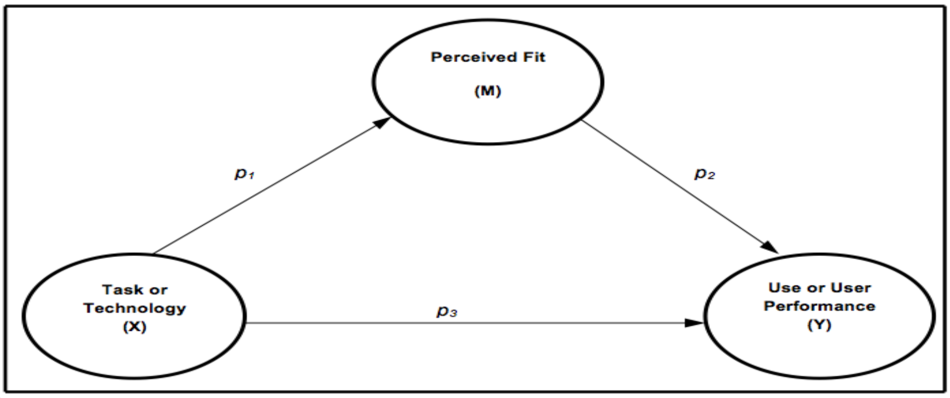

Figure N.1. Generic Mediator Model

Mediation analyses are typically used to address the following questions (Hair et al., 2014, p. 223):

1. Is the direct effect p_3, of the task or technology (X), on use or user performance (Y), significant when the mediator perceived fit (M), is excluded from the path model?
2. Is the indirect effect ($p_1 \cdot p_2$), of the task and technology (X), on use or user performance (Y), through the mediator perceived fit (M), significant after its inclusion in the path model?
3. How much of the direct effect p_3, of the task or technology (X), on use or user performance (Y), does the indirect effect ($p_1 \cdot p_2$), absorb? Is there full or partial mediation?

To test mediating effects, researchers must bootstrap[102] the sampling distribution of the indirect effect, a technique used to examine simple and multiple mediator models

[101] For a generic mediator model, see Hair, Hult, Ringle and Sarstedt (2014, p. 220).
[102] Since bootstrapping has no assumptions of the sampling distribution of statistics, it is compatible with Partial Least Squares – Structural Equation Modeling (Hair et al., 2014). Moreover, this technique yields greater statistical power than traditional methods such as the Sobel Test (Sobel, 1982).

(Preacher and Hayes, 2004, 2008). To use this technique, the following procedure[103] is followed:

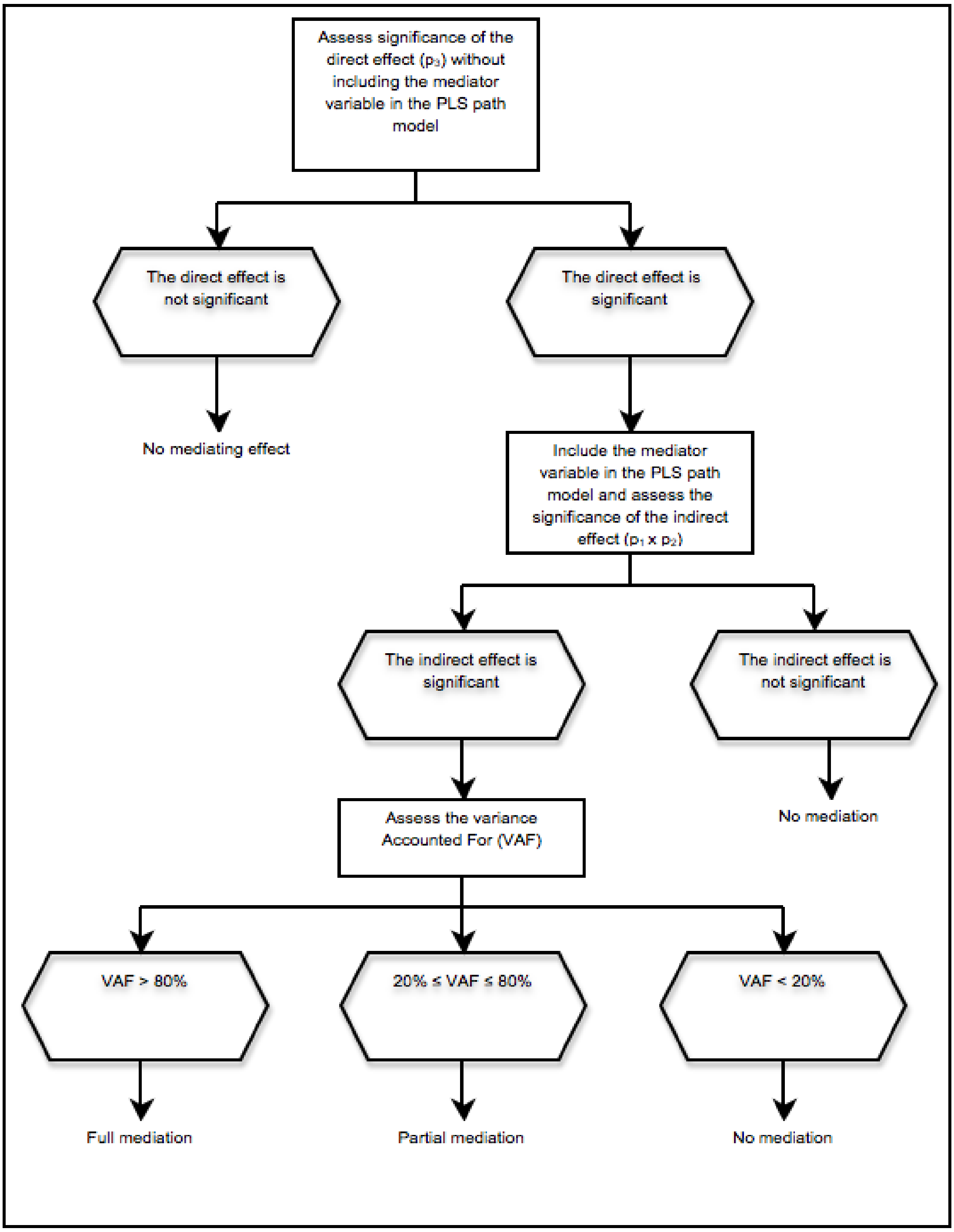

Figure N.2. Mediator Analysis Procedure (Hair, Hult, Ringle and Sarstedt, 2014, p. 218)

[103] Alternatively, a single structural path model with direct and indirect effects (with and without mediators) can be assessed for path significance. As such, the first step can be skipped, and mediators included.

The above procedure was used can be used to examine multiple mediator structural path models. There are two benefits of specifying and testing single multiple mediation models. First, testing the total indirect effect of a predictor (X) on a criterion (Y), is the equivalent of regression analysis using several predictors to determine an outcome. If there is a significant effect, it can be concluded that a set of variables mediates the effect of the predictor (X) on the criterion (Y). Second, it is possible to determine to what extent specific mediator (M) variables, mediate the effect of the predictor (X) on (Y), in relation to the presence of co-mediators. A multiple mediator structural path model, was estimated to examine the four variables of perceived time criticality fit, perceived interdependence fit, perceived mobility fit, and perceived information dependency fit, for total direct and indirect effects. There are 56 paths, representing 8 sets of direct effects, in the multiple mediation model.

The total direct effect of task characteristics, on perceived fit, was calculated using the following expression:

(Time Criticality → Perceived Time Criticality Fit) + (Interdependence → Perceived Time Criticality Fit) + (Mobility → Perceived Time Criticality Fit) + (Information Dependency → Perceived Time Criticality Fit) + (Time Criticality → Perceived Interdependence Fit) + (Interdependence → Perceived Interdependence Fit) + (Mobility → Perceived Interdependence Fit) + (Information Dependency → Perceived Interdependence Fit) + (Time Criticality → Perceived Mobility Fit) + (Interdependence → Perceived Mobility Fit) + (Mobility → Perceived Mobility Fit) + (Information Dependency → Perceived Mobility Fit).

The total direct effect of technology characteristics, on perceived fit, was calculated using the following expression:

(Time Criticality Support → Perceived Time Criticality Fit) + (Interdependence Support → Perceived Time Criticality Fit) + (Mobility Support → Perceived Time Criticality Fit) + (Information Dependency Support → Perceived Time Criticality Fit) + (Time Criticality Support → Perceived Interdependence Fit) + (Interdependence Support → Perceived Interdependence Fit) + (Mobility Support → Perceived Interdependence Fit) + (Information Dependency Support → Perceived Interdependence Fit) + (Time Criticality Support → Perceived Mobility Fit) + (Interdependence Support → Perceived Mobility Fit) + (Mobility Support → Perceived Mobility Fit) + (Information Dependency Support → Perceived Mobility Fit).

The total direct effect of perceived fit, on use, was calculated using the following expression:

(Perceived Time Criticality Fit → Use) + (Perceived Interdependence Fit → Use) + (Perceived Mobility Fit → Use) + (Perceived Information Dependency Fit → Use).

The total direct effect of perceived fit, on user performance, was calculated using the following expression:

(Perceived Time Criticality Fit → User Performance) + (Perceived Interdependence Fit → User Performance) + (Perceived Mobility Fit → User Performance) + (Perceived Information Dependency Fit → User Performance).

The total direct effect of task characteristics, on use, was calculated using the following expression:

(Time Criticality → Use) + (Interdependence → Use) + (Mobility → Use) + (Information Dependency → Use).

The total direct effect of task characteristics, on user performance, was calculated using the following expression:

(Time Criticality → User Performance) + (Interdependence → User Performance) + (Mobility → User Performance) + (Information Dependency → User Performance).

The total direct effect of technology characteristics, on use, was calculated using the following expression:

(Time Criticality Support → Use) + (Interdependence Support → Use) + (Mobility Support → Use) + (Information Dependency Support → Use).

The total direct effect of technology characteristics, on user performance, was calculated using the following expression:

(Time Criticality Support → User Performance) + (Interdependence Support → User Performance) + (Mobility Support → User Performance) + (Information Dependency Support → User Performance).

There are 4 sets, each representing 16 indirect effects, in the multiple mediation model. The total indirect effect of task characteristics on use, through perceived fit, was calculated using the following expression:

(Time Criticality → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Time Criticality → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Time Criticality → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Time Criticality → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Interdependence → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Interdependence → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Interdependence → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Interdependence → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Mobility → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Mobility → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Mobility → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Mobility → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Information Dependency → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Information Dependency → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Information Dependency → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Information Dependency → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use).

The total indirect effect of task characteristics on user performance, through perceived fit, was calculated using the following expression:

(Time Criticality Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Time Criticality Support → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Time Criticality Support → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Time Criticality Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Interdependence Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Interdependence Support → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Interdependence Support → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Interdependence Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Mobility Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Mobility Support → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Mobility Support → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Mobility Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use) + (Information Dependency Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → Use) + (Information Dependency Support → Perceived Interdependence Fit * Perceived Interdependence Fit → Use) + (Information Dependency Support → Perceived Mobility Fit * Perceived Mobility Fit → Use) + (Information Dependency Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → Use).

The total indirect effect of task characteristics on user performance, through perceived fit, was calculated using the following expression:

(Time Criticality → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Time Criticality → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Time Criticality → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Time Criticality → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) +

(Interdependence → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Interdependence → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Interdependence → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Interdependence → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) + (Mobility → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Mobility → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Mobility → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Mobility → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) + (Information Dependency → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Information Dependency → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Information Dependency → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Information Dependency → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance).

The total indirect effect of technology characteristics on user performance, through perceived fit, was calculated using the following expression:

(Time Criticality Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Time Criticality Support → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Time Criticality Support → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Time Criticality Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) + (Interdependence Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Interdependence Support → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Interdependence Support → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Interdependence Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) + (Mobility Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Mobility Support → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Mobility Support → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Mobility Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance) + (Information Dependency Support → Perceived Time Criticality Fit * Perceived Time Criticality Fit → User Performance) + (Information Dependency Support → Perceived Interdependence Fit * Perceived Interdependence Fit → User Performance) + (Information Dependency Support → Perceived Mobility Fit * Perceived Mobility Fit → User Performance) + (Information Dependency Support → Perceived Information Dependency Fit * Perceived Information Dependency Fit → User Performance).

The total direct effects in the multiple mediation model, were calculated based on the following:

$\sum_n = (p_3)$

where:

p_3 = Task or Technology (X) → Use or User Performance (Y)

The total indirect effects in the multiple mediation model, were calculated based on the following:

$\sum_n = (p_1 p_2)$,

where:

p_1 = Task or Technology (X) → Perceived Fit (M)

p_2 = Perceived Fit (M) → Use or User Performance (Y)

The path model for estimation, with eight predictors, four mediator variables, and two criteria, is shown in Figure N.3.

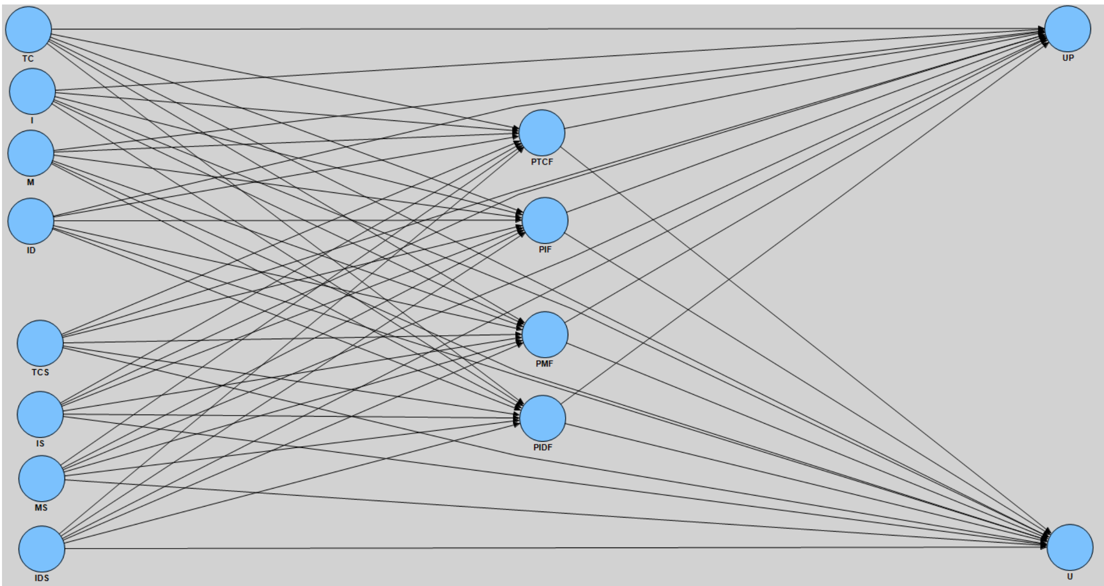

Figure N.3. Screenshot: Multiple Mediator Structural Path Model

Appendix O Task-Technology Fit (TTF) as Covariation

O.1 Reliability, Validity, and Multi-Collinearity

Results of testing reflective manifest indicators of the first-order task and technology characteristics for internal consistency reliability, indicator reliability, and convergent validity (Hair et al., 2014, p. 97), are shown in Table O.1.

Table O.1. Internal Consistency Reliability and Convergent Validity

Latent Variables	Indicators	Outer Loadings	Composite Reliability	AVE
Time Criticality	TC	1.000	1.000	1.000
Interdependence	I	1.000	1.000	1.000
Mobility	M (V)	0.821	0.747	0.598
Information Dependency	M (P)	1.000	1.000	1.000
Time Criticality Support	TCS	1.000	1.000	1.000
Interdependence Support	IS	1.000	1.000	1.000
Mobility Support	MS	1.000	1.000	1.000
Information Dependency Support	I S	1.000	1.000	1.000

Measurement model construct indicators met the criteria for the assessment of internal consistency reliability, indicator reliability, and convergent validity (Hair et al., 2014, p. 107) (refer Figure G.1 of Appendix G).

Results of testing reflective manifest indicators of the first-order task and technology characteristics for discriminant validity using cross-loadings (Hair et al., 2014, p. 97) are shown in Table O.2.

Table O.2. Cross-Loadings								
	TC	**I**	**M**	**ID**	**TCS**	**IS**	**MS**	**IDS**
TC	**1.000**	0.274	0.207	0.220	0.225	0.207	0.204	0.145
I	0.274	**1.000**	0.106	0.199	0.145	0.231	0.128	0.117
M (V)	0.150	0.041	**0.722**	0.052	0.108	0.156	0.023	0.077
M (P)	0.164	0.116	**0.821**	0.122	0.103	0.140	0.145	0.053
ID	0.220	0.199	0.116	**1.000**	0.231	0.230	1.000	0.295
TCS	0.225	0.145	0.136	0.231	**1.000**	0.337	0.302	0.427
IS	0.207	0.231	0.189	0.230	0.337	**1.000**	0.429	0.351
MS	0.204	0.128	0.116	0.204	0.302	0.429	**1.000**	0.295
IDS	0.145	0.117	0.351	0.218	0.427	0.351	0.295	**1.000**

* SIC = Single Item Construct. Shaded diagonal cells represent square roots of construct AVE values.

TC = Time Criticality, I = Interdependence, M (V) = Mobility (Variety), M (P) = Mobility (Proximity), ID = Information Dependency,
TCS = Time Criticality Support, IS = Interdependence Support, MS = Mobility Support (MS), IDS = Information Dependency Support (IDS)

Results of testing reflective manifest indicators of the first-order task and technology characteristics for discriminant validity using the Fornell-Larker Criterion (Hair et al., 2014, p. 97) are shown in Table O.3.

Table O.3. Fornell-Larker Criterion Results								
	TC	**I**	**M**	**ID**	**TCS**	**IS**	**MS**	**IDS**
TC	SIC*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
I	0.274	SIC*	0.000	0.000	0.000	0.000	0.000	0.000
M	0.203	0.106	0.773	0.000	0.000	0.000	0.000	0.000
ID	0.220	0.199	0.116	SIC*	0.000	0.000	0.000	0.000
TCS	0.225	0.145	0.231	0.231	SIC*	0.000	0.000	0.000
IS	0.207	0.231	0.189	0.230	0.337	SIC*	0.000	0.000
MS	0.204	0.128	0.429	0.204	0.302	0.429	SIC*	0.000
IDS	0.145	0.117	0.082	0.117	0.427	0.351	0.082	SIC*

* SIC = Single Item Construct. Shaded diagonal cells represent square roots of construct AVE values.

TC = Time Criticality, I = Interdependence, M = Mobility, ID = Information Dependency,
TCS = Time Criticality Support, IS = Interdependence Support, MS = Mobility Support (MS), IDS = Information Dependency Support (IDS)

The cross-loadings and Fornell-Larcker criterion results met the criteria for the assessment of discriminant validity (Hair et al., 2014, p. 104) (refer Section G.2 of Appendix G).

Prior to analyses of TTF as internally consistent co-alignment and covariation effects, multiple regressions were run to check the measures of task and technology characteristics for collinearity (Hair et al., 2014, p.123). The results are shown in Table O.4.

Table O.4: First-Order Task and Technology Characteristics of a Second-Order Fit					
Criterion					
Use			**User Performance**		
Predictor	**Tolerance**	**VIF**	**Predictor**	**Tolerance**	**VIF**
Time Criticality	0.842	1.188	*Time Criticality*	0.842	1.188
Interdependence	0.881	1.136	*Interdependence*	0.881	1.136
Mobility	0.931	1.074	*Mobility*	0.931	1.074
Information Dependence	0.873	1.146	*Information Dependence*	0.873	1.146
Time Criticality Support	0.741	1.349	*Time Criticality Support*	0.741	1.349
Interdependence Support	0.705	1.419	*Interdependence Support*	0.705	1.419
Mobility Support	0.766	1.305	*Mobility Support*	0.766	1.305
Information Dependence Support	0.753	1.328	*Information Dependence Support*	0.753	1.328

TTF was tested first as internally consistent co-alignment, and second, for its covariation effects on use and user performance. A screenshot of the estimated structural path model representing ‘fit’ as co-alignment and internal consistency is depicted in Figures O.1. and O2 respectively.

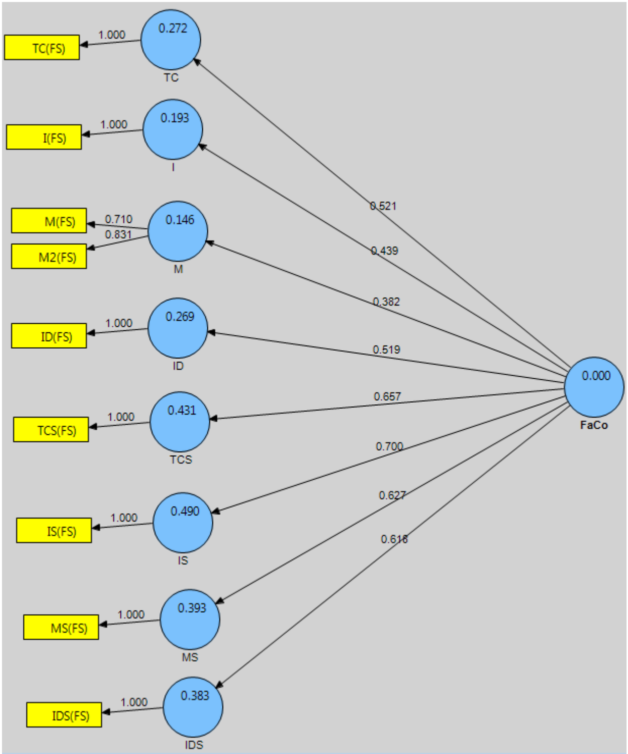

Figure O.1. Fit as Internally Consistent Co-alignment

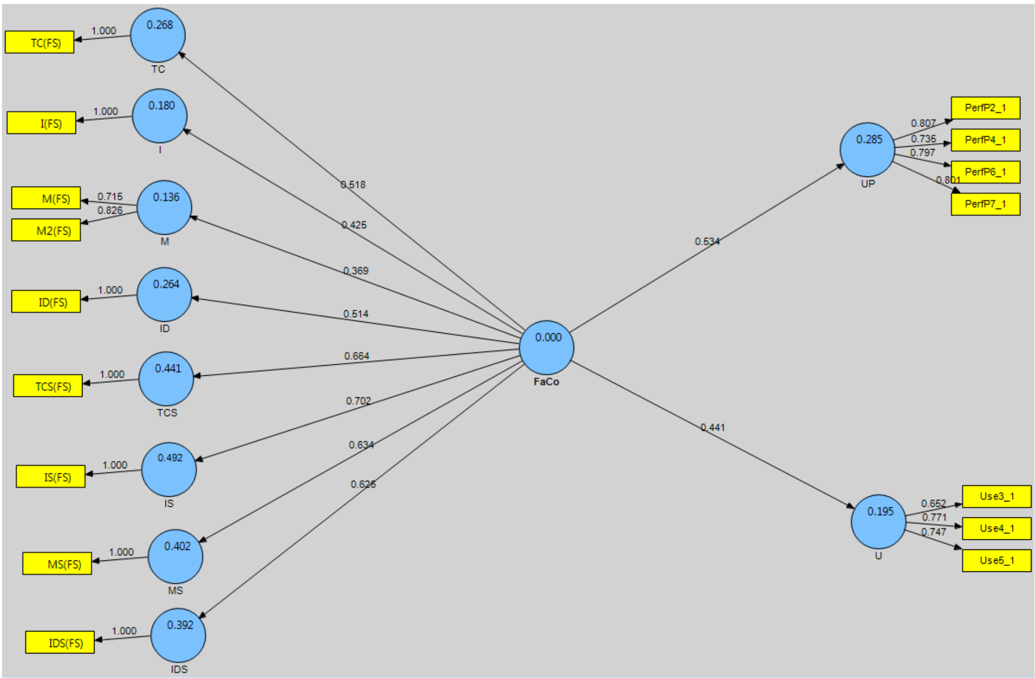

Figure O.2. Covariation Effects of Fit as Internally Consistent Co-alignment on Use and User Performance

O.2 The Modeling of Co-Alignment: A Snapshot of Prior ‘Fit’ Model Specifications

In the extant literature on ‘fit as covariation’, it appears that in prior works, there have been inconsistent specifications of conceptualized and tested ‘fit’ co-alignment models. The following are observations:

Venkatraman (1989) appears to have proposed a <u>formative</u> second-order ‘fit as coalignment’ (p. 437), as depicted in Figure O.3.

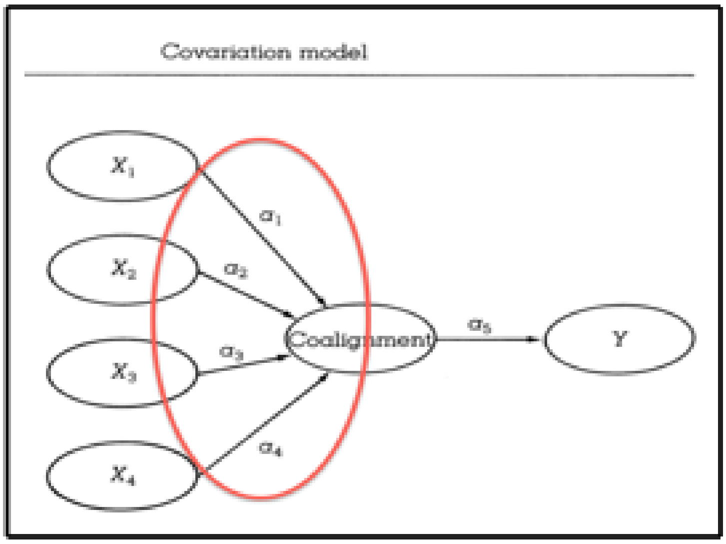

Figure O.3 ‘Fit’ as Covariation (Coalignment) Model (Venkatraman, 1989, p. 437)

This model-type has been adopted in some subsequent works, in which ‘fit as covariation’ has been conceptualized e.g. Bergeron et al’s (2001) study, in which it appears that Venkatraman’s (1989) second-order <u>formative</u> ‘fit’ co-alignment construct was adopted (p. 135), as depicted in Figure O.4.

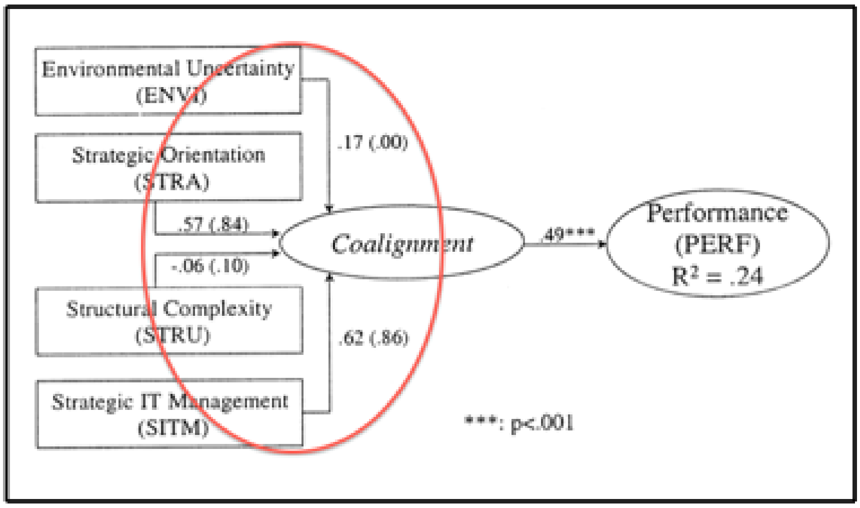

Figure O.4 ‘Fit’ as Covariation (Coalignment) Model (Bergeron et al., 2001, p. 135)

However, Venkatraman (1990) tested a second-order reflective ‘fit’ co-alignment construct, as depicted below (Figure O.5) in a reflective-reflective (Type I) co-alignment model setup, observing that empirical support is provided by the ‘statistical significance of the three parameters y_1, y_2, and y_3, representing loadings of the three dimensions’ (reflectively measured), ‘on the second-order factor’ (reflectively measured) ‘of co-alignment’ (p. 32).

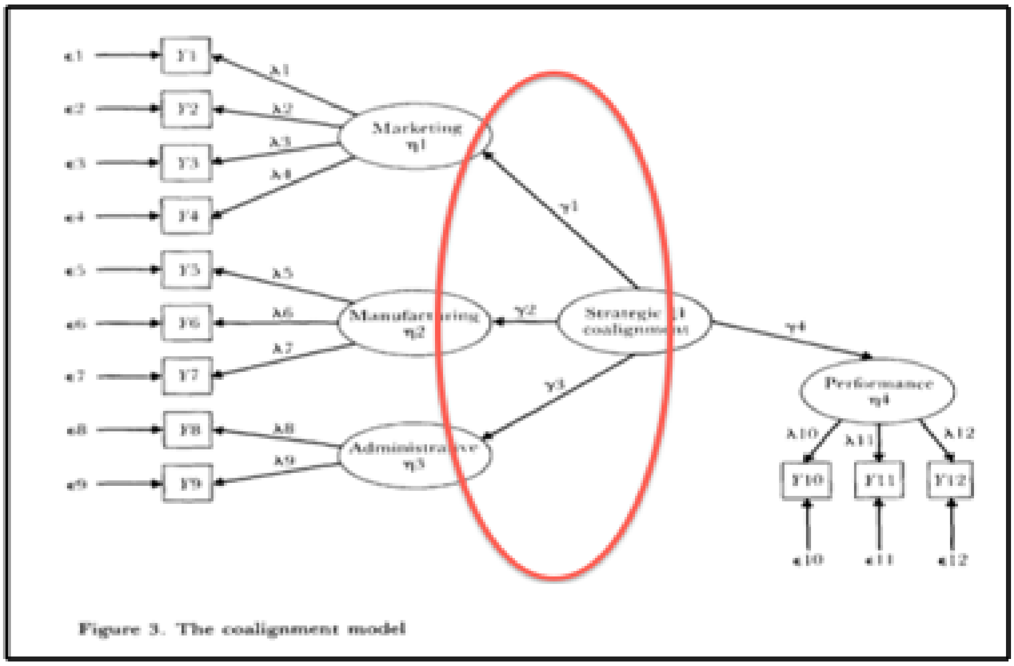

Figure 3. The coalignment model

Figure O.5 The ‘Fit’ Co-alignment Model (Venkatraman, 1990, p. 32)

Apparently, a similar approach (reflective second-order factor) to modeling 'fit' as co-alignment is what appears to have been adopted in Segars, Grover and Teng's (1998) paper, where they tested what they termed as a model of 'internal co-alignment (p. 329), as depicted in Figure O.6.

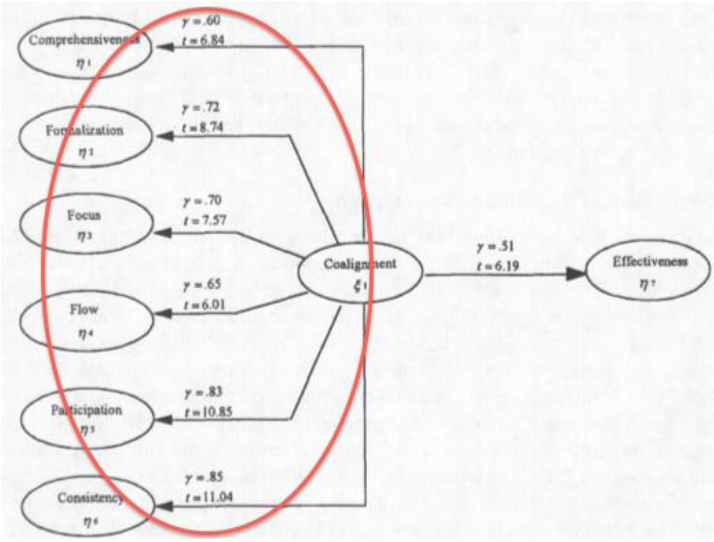

Figure O.6 'Fit' as Internal Co-alignment (Segars, Grover and Teng, p. 329)

This approach was similarly used in Wang et al's (2008) paper, in which the effects of 'fit' as 'consistency' were tested (p. 1618), as depicted in Figure O.7.

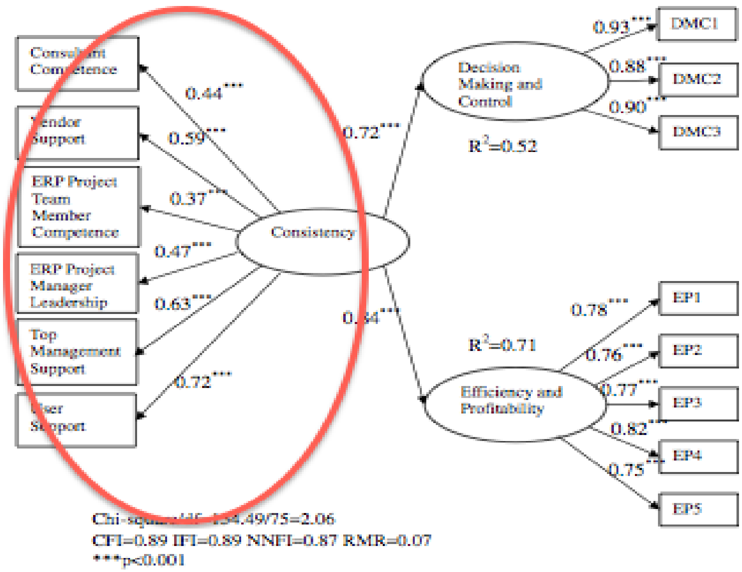

Fig. 2. Structural equation model of consistency in ERP project.

Figure O.7 'Fit' as Consistency (Wang, Shih, Jiang and Klein, 2008, p. 1618)

Having considered cited literature on approaches to the modeling of a ‘co-alignment’ fit, and in recognizing a seemingly more appropriate representation of ‘co-alignment’ and ‘internal consistency’, the researcher arrived at the informed decision to adopt a ‘reflective-reflective’ (Type I) model type (Jarvis et al., 2003, p. 205; Becker et al., 2012, p. 363). This was to ensure the precise and appropriate specification of models of internally consistent co-alignment expressed as a set of observed first-order factors in terms of a ‘fit’ as an unobserved second-order factor (Venkatraman, 1990, Segars, 1994, Segars et al., 1998), which is subsequently tested for its effects on the criteria variables of use and user performance. Accordingly, the TTF models tested for internally consistent co-alignment and covariation effects on use and user performance, were specified and estimated using the reflective-reflective (Type I) ‘fit’ covariation path model configuration, as depicted in Figure O.8.

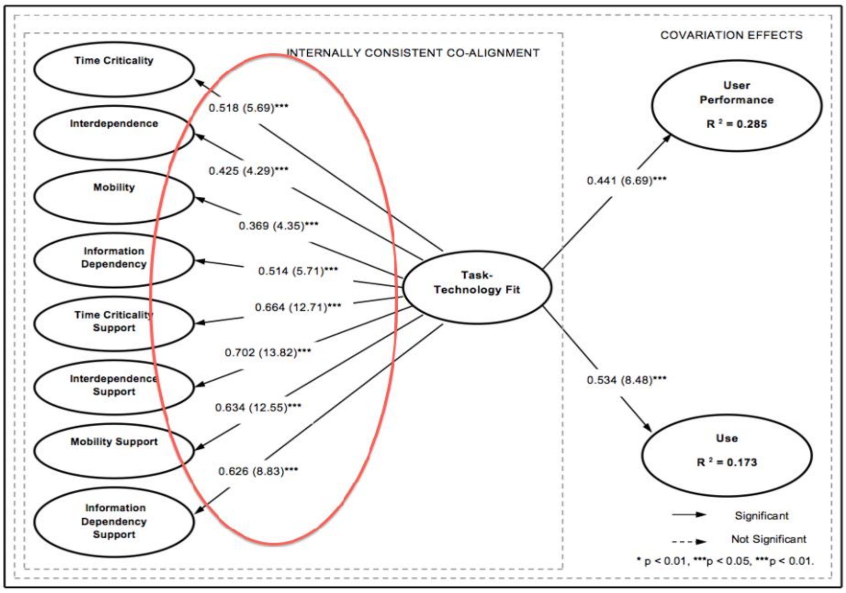

Figure O.8 The Covariation Effects of ‘Task-Technology Fit (TTF)’ as Internally Consistent Co-alignment (Chapter 9)

Appendix P Cover Letter and Survey Instrument (1)

Dear Sir/Madam,

My name is Maradona Gatara, and I am a Doctoral student in Information Systems (IS) at the University of the Witwatersrand (WITS), Johannesburg.

As a PhD degree requirement at WITS, I am conducting a study on mobile-technology enabled healthcare service delivery systems for Community Health Worker (CHW) performance.

You are invited to take part in this study by completing this questionnaire. There are no right or wrong answers.

Participation in this survey is completely voluntary and involves no risk, penalty or loss of benefits.

You will not be required to provide your personal details or reveal your identity while answering the questionnaire.

The survey is both confidential and anonymous, and the data collected will only be used for the study and no other purpose.

The survey questionnaire consists of 84 statements. Please circle the number that reflects the extent to which you agree or disagree with each statement.

The survey has been unconditionally approved by the WITS Human Research Ethics Committee (protocol number: H13/08/42).

The entire questionnaire should take 45 minutes to complete. Completion of this questionnaire will be taken as your consent to participate.

Should you have any queries or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 93 204 215.

You can also reach me through email correspondence at maradonagatara@gmail.com.

Thank you for considering your participation

Yours Sincerely,

Maradona C. Gatara
Ph. D. Candidate
Department of Information Systems (IS),
School of Economic and Business Sciences (SEBS),
University of the Witwatersrand (WITS),
Johannesburg, South Africa (SA)

SECTION 1: COMMUNITY HEALTH WORKER (CHW) PROFILE

1. Please indicate your age by ticking the appropriate box.

☐ Below 25 years
☐ 25-34 years
☐ 35-44 years
☐ 45-54 years
☐ 55-64 years
☐ 65 years and above
☐ Prefer not to say

2. Please indicate your gender by ticking the appropriate box.

☐ Male
☐ Female
☐ Prefer not to say

3. Please indicate your years of experience as a Community Health Worker (CHW): ______ years.
4. Please indicate your highest level of education by ticking the appropriate box.

☐ Secondary School
☐ Post-Secondary Diploma
☐ Undergraduate Degree
☐ Postgraduate Diploma
☐ Postgraduate Degree

5. Please indicate how long you have been using the mHealth tool by ticking the appropriate box.

☐ Less than 1 month
☐ 1-2 months
☐ 3-4 months
☐ 5 or more months

SECTION 2: HEALTHCARE SERVICE TASKS

1. Please indicate whether you use the mHealth tool in the following healthcare service areas. You may tick more than one task.

	Monitoring Tasks	**Prevention Tasks**	**Referral Tasks**
Nutritional Care			
Hygiene and Sanitation			
Referral			
Fever and Malaria			
HIV/AIDS			
TB Care			
Neonatal Care			
Maternal Care			
Family Planning			
Other (specify)			

2. Please circle the average time window (from start to finish) within which you must complete your tasks in the selected healthcare service area(s).

	No time restriction	**Within a week**	**Within a few days**	**Within a day**	**Within a few hours**	**Within an hour**	**Within 10 minutes**
Nutritional care	1	2	3	4	5	6	7
Hygiene and sanitation	1	2	3	4	5	6	7
Fever and malaria	1	2	3	4	5	6	7
HIV/AIDS care	1	2	3	4	5	6	7
TB care	1	2	3	4	5	6	7
Neonatal care	1	2	3	4	5	6	7
Maternal care	1	2	3	4	5	6	7
Family planning care	1	2	3	4	5	6	7
Other (specify):	1	2	3	4	5	6	7

3. After first becoming aware of the need to perform the following tasks, how urgently do you need to START them?

	I can allow a long delay before starting (take it easy)	**I can allow a delay before starting**	**I can allow only a small delay before starting**	**I must start as soon as possible.**	**I must start almost immediately**	**I must start in a hurry**
Monitoring Task	1	2	3	4	5	6
Health Promotion Task	1	2	3	4	5	6
Referral Task	1	2	3	4	5	6

4. After starting to perform the following tasks, how urgently do you need to FINISH them?

	I can allow a long delay before finishing (take it easy)	**I can allow a delay before finishing**	**I can allow only a small delay before finishing**	**I must finish as soon as possible**	**I must finish almost immediately after I start.**	**I must finish very urgently**
Monitoring Task	1	2	3	4	5	6
Prevention Task	1	2	3	4	5	6
Referral Task	1	2	3	4	5	6

5. Please circle the number that reflects the extent to which you agree with the following statements relating to your tasks as a CHW.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	It is very important for me to start my tasks on time.	1	2	3	4	5	6	7
b.	It is very important for me to complete my tasks on time.	1	2	3	4	5	6	7
c.	It is very important for me to start my tasks as soon as possible.	1	2	3	4	5	6	7
d.	It is very important for me to finish my tasks as soon as possible.	1	2	3	4	5	6	7
e.	It is very important for me to take immediate action.	1	2	3	4	5	6	7
f.	It is very important for me to promptly respond to emergencies.	1	2	3	4	5	6	7

6. Please circle the number that reflects the extent to which you agree with the following statements relating to your tasks as a CHW.

		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	I often need to complete my tasks with co-workers.	1	2	3	4	5	6	7
b.	I often need to share information with co-workers.	1	2	3	4	5	6	7
c.	I often need to rely on the work of other CHWs.	1	2	3	4	5	6	7
d.	I often need to use information received from co-workers.	1	2	3	4	5	6	7
e.	I often need to depend on the efforts of other CHWs.	1	2	3	4	5	6	7

7. In the selected healthcare service areas, do you perform the following tasks in a specific location or several locations?

	I perform my tasks in the same location	I perform my tasks in very few locations	I perform my tasks in a few locations	I perform my tasks in many locations	I perform my tasks in very many locations	I perform my tasks in any given location where my services are required
Monitoring Tasks	1	2	3	4	5	6
Promotion Tasks	1	2	3	4	5	6
Referral Tasks	1	2	3	4	5	6
Other (specify)	1	2	3	4	5	6

8. Please circle the number that reflects the extent to which you agree with the following statements relating to your tasks as a CHW.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly agree**
a.	I often need to perform my tasks in several places.	1	2	3	4	5	6	7
b.	I often need to work away from just one single place for long periods.	1	2	3	4	5	6	7
c.	I often need to perform tasks in locations that are far from my Community Health Unit (CHU).	1	2	3	4	5	6	7
d.	I often need to travel to remote locations to perform tasks.	1	2	3	4	5	6	7

9. Please circle the number that reflects the extent to which you agree with the following statements relating to your need to depend on information as you perform your tasks.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	I often need to depend on information on my current location.	1	2	3	4	5	6	7
b.	I often need to depend on information on the location of supplies.	1	2	3	4	5	6	7
c.	I often need to depend on information on the location of households.	1	2	3	4	5	6	7

SECTION 3: MOBILE HEALTH TOOL FEATURES

1. Please circle the number that reflects the extent to which you agree with the following statements related to your mHealth tool (mobile phone).

		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The mHealth tool works well in providing timely notification of required urgent actions.	1	2	3	4	5	6	7
b.	The mHealth tool effectively responds to my requests quickly.	1	2	3	4	5	6	7
c.	The mHealth tool notifies me of emergencies in a timely manner.	1	2	3	4	5	6	7

2. Please circle the number that reflects the extent to which you agree with the following statements relating to features of the mHealth tool.

		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The mHealth tool makes it easy to share information with others.	1	2	3	4	5	6	7
b.	The mHealth tool effectively compiles data from co-workers.	1	2	3	4	5	6	7
c.	The mHealth tool effectively pulls together data from co-workers.	1	2	3	4	5	6	7
d.	The mHealth tool effectively integrates data from co-workers.	1	2	3	4	5	6	7

3. Please circle the number that reflects the extent to which you agree with the following statements relating to features of the mHealth tool.

		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The mHealth tool effectively responds to changes in location.	1	2	3	4	5	6	7
b.	The mHealth tool operates reliably as I move to different places.	1	2	3	4	5	6	7
c.	The mHealth tool flexibly adjusts as I move from one place to another.	1	2	3	4	5	6	7
d.	The mHealth tool effectively adapts to my movement from one place to another.	1	2	3	4	5	6	7

4. Please circle the number that reflects the extent to which you agree with the following statements relating to features of the mHealth tool.

		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The mHealth tool easily provides information on my current location.	1	2	3	4	5	6	7
b.	The mHealth tool makes information on the location of households very accessible.	1	2	3	4	5	6	7
c.	The mHealth tool makes information on the location of supplies readily accessible.	1	2	3	4	5	6	7

SECTION 4: FIT

1. Please circle the number that reflects the extent to which you agree with the following statements relating to the extent to which the mHealth tool (mobile phone) support functions fit your work.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	The mHealth tool supports me in starting my tasks on time.	1	2	3	4	5	6	7
b.	The mHealth tool supports me in finishing my tasks on time.	1	2	3	4	5	6	7
c.	The mHealth tool supports me during urgent interventions.	1	2	3	4	5	6	7
d.	The mHealth tool supports me in promptly responding to emergencies.	1	2	3	4	5	6	7
e.	The mHealth tool supports me in completing tasks with co-workers.	1	2	3	4	5	6	7
f.	The mHealth tool supports me in information sharing with co-workers.	1	2	3	4	5	6	7
g.	The mHealth tool supports me in working with other CHWs.	1	2	3	4	5	6	7
h.	The mHealth tool supports me in receiving information from co-workers.	1	2	3	4	5	6	7
i.	The mHealth tool supports me in performing tasks at several locations.	1	2	3	4	5	6	7
j.	The mHealth tool supports me in working away from just one place for long periods.	1	2	3	4	5	6	7
k.	The mHealth tool supports me in working away form my Community Unit (CU).	1	2	3	4	5	6	7
l.	The mHealth tool supports me in travelling to remote locations to perform tasks.	1	2	3	4	5	6	7
m.	The mHealth tool supports me in accessing information on my current location.	1	2	3	4	5	6	7
n.	The mHealth tool supports me in accessing information on the location of households.	1	2	3	4	5	6	7
o.	The mHealth tool supports me in accessing information on the location of supplies.	1	2	3	4	5	6	7
p.	The mHealth tool supports me in accessing information on the locations I travel to.	1	2	3	4	5	6	7

SECTION 5: USE OF MOBILE (PHONE) HEALTH TOOL

1. On average, how often do you use the mHealth tool (mobile phone) to perform your tasks? Please circle ONE number only.

   a. Almost never
   b. Less than once a month
   c. Once a month
   d. A few times a month
   e. A few times a week
   f. About once a day
   g. Several times a day

2. On average, how much time do you spend each day you use the mHealth tool (mobile phone) to perform your tasks? Please circle ONE number only.

   a. Almost never
   b. Less than ½ an hour
   c. From ½ an hour to 1 hour
   d. 1-2 hours
   e. 2-3 hours
   f. More than 3 hours

3. Please circle the number that reflects the extent to which you agree or disagree with the following statements on your use of the mHealth tool (mobile phone) to perform tasks.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	I am very dependent on the mHealth tool to perform tasks.	1	2	3	4	5	6	7
b.	My work is dependent on using the mHealth tool to perform tasks.	1	2	3	4	5	6	7
c.	Using the mHealth tool allows me to do more than would be possible without it.	1	2	3	4	5	6	7

4. Please circle the number that reflects the extent to which you agree or disagree with the following statements on your use of the mHealth tool (mobile phone) to perform tasks.

		Strongly disagree	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	I like using the mHealth tool.	1	2	3	4	5	6	7
b.	I look forward to using the mHealth tool.	1	2	3	4	5	6	7
c.	Using the mHealth tool is frustrating.	1	2	3	4	5	6	7
d.	Once I start using the mHealth tool, I find it hard to stop.	1	2	3	4	5	6	7
e.	I get bored quickly when using the mHealth tool.	1	2	3	4	5	6	7

5. Please circle the number that reflects the extent to which you agree or disagree with the following statements on your use of the mHealth tool (mobile phone) to perform tasks.

No		**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
a.	I have the resources required to use the mHealth tool.	1	2	3	4	5	6	7
b.	I have the knowledge required to use the mHealth tool.	1	2	3	4	5	6	7
c.	With the required training, it would be easy for me to use the mHealth tool.	1	2	3	4	5	6	7
d.	The mHealth tool does not complement paper-based systems I use.	1	2	3	4	5	6	7

SECTION 6: PERFORMANCE

1. Please circle the number that reflects the extent to which you agree or disagree with the following statements on your use of the mHealth tool to perform tasks.

No		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The mHealth tool increases my productivity.	1	2	3	4	5	6	7
b.	The mHealth tool increases my effectiveness with patients.	1	2	3	4	5	6	7
c.	The mHealth tool increases my quality of patient care.	1	2	3	4	5	6	7
d.	The mHealth tool saves me time.	1	2	3	4	5	6	7
e.	The mHealth tool enables me to complete tasks more quickly.	1	2	3	4	5	6	7
f.	Using the mHealth tool improves my effectiveness in completing tasks.	1	2	3	4	5	6	7
g.	The mHealth tool improves the quality of my tasks.	1	2	3	4	5	6	7
h.	The mHealth tool decreases my reporting errors.	1	2	3	4	5	6	7

Mobile Health (Phone) Tool Reporting

1. How many households do you visit per month? ______ households

2. What percentage of the households visited are you able to report? Please tick the appropriate box.

☐ 0-20% ☐ 41-60% ☐ 81-100%
☐ 21-40% ☐ 61-80%

3. Of the households visited, how many of the following cases do you report per month?

Monitoring Cases	Health Promotion Cases	Referral Cases	Other (specify)

4. In a typical week, how much time (in hours) do you take to complete reports for cases?

Monitoring Cases	Health Promotion Cases	Referral Cases	Other (specify)

5. Of the cases reported per month, approximately what percentage are completed on time?

☐0-10% ☐20-30% ☐40-50% ☐60-70% ☐80-90%

☐10-20% ☐30-40% ☐50-60% ☐70-80% ☐90-100%

6. Of the reports completed for all cases per month, what percentage are complete (i.e no missing data)?

☐0-10% ☐20-30% ☐40-50% ☐60-70% ☐80-90%

☐10-20% ☐30-40% ☐50-60% ☐70-80% ☐90-100%

7. What percentage of the reports completed are returned to you for additional information due to errors or inconsistencies?

☐0-10% ☐20-30% ☐40-50% ☐60-70% ☐80-90%

☐10-20% ☐30-40% ☐50-60% ☐70-80% ☐90-100%

Appendix Q Cover Letter and Survey Instrument (2)

Dear Sir/Madam,

My name is Maradona Gatara, and I am a Doctoral student in Information Systems (IS) at the University of the Witwatersrand (WITS), Johannesburg.

As a PhD degree requirement at WITS, I am conducting a study on mobile-technology enabled healthcare service delivery systems for Community Health Worker (CHW) performance, involving the use of paper-based systems for patient care.

You are invited to take part in this study by completing this questionnaire. There are no right or wrong answers.

Participation in this survey is completely voluntary and involves no risk, penalty or loss of benefits.

You will not be required to provide your personal details or reveal your identity while answering the questionnaire.

The survey is both confidential and anonymous, and the data collected will only be used for the study and no other purpose.

The survey questionnaire consists of 18 statements. Please circle the number that reflects the extent to which you agree or disagree with each statement.

The survey has been unconditionally approved by the WITS Human Research Ethics Committee, (protocol number: H13/08/42).

The entire questionnaire should take 20 minutes to complete. Completion of this questionnaire will be taken as your consent to participate. Should you have any queries or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 93 204 215.

You can also reach me through email correspondence at maradonagatara@gmail.com.

Thank you for considering your participation

Yours Sincerely,

Maradona C. Gatara
Ph. D. Candidate
Department of Information Systems (IS),
School of Economic and Business Sciences (SEBS),
University of the Witwatersrand (WITS),
Johannesburg, South Africa (SA)

SECTION 1: CHW PROFILE

1. Please indicate your age bracket by ticking the appropriate box.

☐ Below 25 years
☐ 25-34 years
☐ 35-44 years
☐ 45-54 years
☐ 55-64 years
☐ 65 years and above
☐ Prefer not to say

2. Please indicate your gender by ticking the appropriate box.

☐ Male
☐ Female
☐ Prefer not to say

3. Please indicate your years of experience as a Community Health Worker (CHW) _____ years.

4. Please indicate your highest level of education by ticking the appropriate box.

☐ Secondary School
☐ Post-Secondary Diploma
☐ Undergraduate Degree
☐ Postgraduate Diploma
☐ Postgraduate Degree

5. Please indicate how long you have been using the MOH tool by ticking the appropriate box.

☐ Less than 1 month
☐ 1-2 months
☐ 3-4 months
☐ 5 or more months

SECTION 2: HEALTHCARE SERVICE TASKS

10. Please indicate whether you use the MOH tool in the following healthcare service areas. You may tick more than one task.

	Monitoring Tasks	**Health Promotion Tasks**	**Referral Tasks**
Nutritional Care			
Hygiene and Sanitation			
Referral			
Fever and Malaria			
HIV/AIDS			
TB Care			
Neonatal Care			
Maternal Care			
Family Planning			
Other (specify)			

SECTION 3: INDIVIDUAL PERFORMANCE

1. Please circle the number that reflects the extent to which you agree or disagree with the following statements on your use of the MOH tool to perform tasks.

No		Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
a.	The MOH tool increases my productivity.	1	2	3	4	5	6	7
b.	The MOH tool increases my effectiveness with patients.	1	2	3	4	5	6	7
c.	The MOH tool increases my quality of patient care.	1	2	3	4	5	6	7
d.	The MOH tool saves me time.	1	2	3	4	5	6	7
e.	The MOH tool enables me to complete tasks more quickly.	1	2	3	4	5	6	7
f.	Using the MOH tool improves my effectiveness in completing tasks.	1	2	3	4	5	6	7
g.	The MOH tool improves the quality of my tasks.	1	2	3	4	5	6	7
h.	The MOH tool decreases my reporting errors.	1	2	3	4	5	6	7

MOH Tool Reporting

1. How many households do you visit per month? ______ households

2. What percentage of the households visited are you able to report? Please tick the appropriate box.

☐ 0-20% ☐ 41-60% ☐ 81-100%
☐ 21-40% ☐ 61-80%

3. Of the households visited, how many of the following cases do you report per month?

Monitoring Cases	Health Promotion Cases	Referral Cases	Other (specify)

4. In a typical week, how much time (in hours) do you take to complete reports for cases?

Monitoring Cases	Health Promotion Cases	Referral Cases	Other (specify)

5. Of the cases reported per month, approximately what percentage are completed on time?

☐ 0-10% ☐ 20-30% ☐ 40-50% ☐ 60-70% ☐ 80-90%

☐ 10-20% ☐ 30-40% ☐ 50-60% ☐ 70-80% ☐ 90-100%

6. Of the reports completed for all cases per month, what percentage are complete (i.e no missing data)?

☐ 0-10% ☐ 20-30% ☐ 40-50% ☐ 60-70% ☐ 80-90%

☐ 10-20% ☐ 30-40% ☐ 50-60% ☐ 70-80% ☐ 90-100%

8. What percentage of the reports completed are returned to you for additional information due to errors or inconsistencies?

☐ 0-10% ☐ 20-30% ☐ 40-50% ☐ 60-70% ☐ 80-90%

☐ 10-20% ☐ 30-40% ☐ 50-60% ☐ 70-80% ☐ 90-100%

Appendix R Ethics Clearance

Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)
R14/49 Gatara

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER H13/08/42**
PROJECT TITLE	Mobile technology-enabled healthcare service delivery systems for community health workers in Kenya: A technology-to-performance chain perspective
INVESTIGATOR(S)	Mr MC Gatara
SCHOOL/DEPARTMENT	School of Economic and Business Sciences
DATE CONSIDERED	16/08/2013
DECISION OF THE COMMITTEE	Approved Unconditionally
EXPIRY DATE	02/09/2015

DATE 03/09/2013 **CHAIRPERSON** (Professor T Milani)

cc: Supervisor : Prof J Cohen

DECLARATION OF INVESTIGATOR(S)

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10003, 10th Floor, Senate House, University.

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee. **I agree to completion of a yearly progress report.**

Signature

03 / 09 / 2013
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

Appendix S Approval Letter: Data Collection

Division of Community Health Services
"Afya Yetu, Jukumu Letu"

MINISTRY OF HEALTH (MOH)

4th September 2013

Mr. Maradona Charles Gatara,

University of the Witwatersrand (WITS)

Johannesburg, South Africa.

Dear Maradona,

RE: MOBILE-TECHNOLOGY ENABLED HEALTHCARE SERVICE DELIVERY SYSTEMS FOR COMMUNITY HEALTHCARE WORKERS (CHW's) IN KENYA

Following your inquiry and subsequent discussions regarding your proposed study, I wish to confirm that the Ministry of Health - Division of Community Health Services will be pleased to facilitate your field data collection from Community Health Workers in community-based healthcare service delivery projects deployed in their sites. Upon completion of your study, the Division of Community Health Services will be interested in the results of this work. As indicated earlier, you will commence data collection from late September to the end of October – and the Division of Community Health Services will communicate this information to the field staff to facilitate access to the CHW's for the field exercise.

Thank You.

Yours Sincerely

Dr. James Mwitari

Head: Division of Community Health Services (DCHS)

Appendix T Photographs[104] of Field Sites

Figure T.1. Peri-Urban Area: Nandi County Site

[104] Permission to take snapshots of select field study sites were taken in the Counties of Siaya, Nandi, Kilifi, Nairobi, and Nakuru, was granted by the Ministry of Health (MOH) Division of Community Health Services (DCHS). In addition, the participants involved gave full consent for their photographs to be taken.

Figure T.2. Siaya County Site

Figure T.3. Peri-Urban Area: Nakuru County

Figure T.4. Nandi County Site

Figure T.5. Preparatory Site (Millennium Villages Project): Siaya County:

Figure T.6. Peri-Urban Public Health Facility: Nandi County

Figure T.7. Assembled Community Health Worker (CHW) Field Session: Kilifi County

Figure T.8. Assembled Community Health Worker Session: Nairobi County

Figure T.9. Community Health Worker (CHW) Field Briefing: Nakuru County