A SURVEY OF MOBILE HEALTH SYSTEM INFUSION AMONG HEALTHCARE PRACTITIONERS

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Abstract

In recent years, clinicians are beginning to utilise Mobile Health Systems (mobile devices with clinical applications) when delivering healthcare services to patients at the point-of-care. For Mobile Health Systems (MHS) to be truly valuable, it is argued that the technological artefact be utilised post-adoption and embedded within the clinicians’ work practices. Infusion is a post-adoptive phase of the Cooper and Zmud (1990) model whereby potential benefits can be obtained by the user through exhaustive use of the IT. Yet, there is a dearth of research focusing on the benefits derived from MHS infusion. In response, an exploratory study is undertaken in this paper whereby a conceptual model with eleven hypotheses is presented and examined. The empirical findings of the developed infusion model reveal key factors which positively impacts MHS infusion (availability, self-efficacy, time-criticality, habit, technology trust and task behaviour). More specifically, it provides empirical evidence surrounding the benefits which can be obtained through the infusion of MHS by clinicians. This study illustrates that infusion leads to improvements in (1) individual effectiveness in terms of clinical care, (2) efficiency in terms of individuals’ workflow, and (3) learning. As a result, this research study contributes to both theory and practice.

Keywords: Infusion, Mobile Health, Individual, Survey.
1 Introduction and Theoretical Grounding

The history and utilisation of IT in the medical informatics field is well established, advancing from primarily administration - and business-oriented applications to more clinically oriented systems (Giuse and Kuhn, 2003). Since the advent of ‘e-health’, healthcare organisations internationally are continually striving to implement new programs designed to improve patient care and support workflow activities of clinicians (Black et al., 2011). For example, the British National Health Services invested £12.8 billion in a National Programme for Information Technology (NPfIT) and the Obama administration in the United States (US) has similarly committed to a US$38 billion e-health investment in health care (Catwell, 2009). Recent developments in healthcare have witnessed the emergence of ubiquitous computing, namely Mobile Health Systems (MHS). MHS is defined for the purpose of this paper as any mobile handheld device running medical applications which are used as part of clinical practice. The rise in implementing MHS is reflected in the marketplace whereby the m-Health industry is valued between $50 billion and $60 billion globally (McKinsey, 2010). Due to the chaotic nature associated with the delivery of healthcare services the hospital environment appears well suited to the adoption of ubiquitous computing. The underlying premise for this, according to Han et al., (2004), is that patient care in most environments is by its very nature a mobile experience.

The documented success of MHS is purported throughout the information systems and medical informatics fields. Such studies have focused on mobile technology applications from e-mail, voice, SMS (Heinzelmann et al., 2005), inventory management (Freudenheim, 2004; Bhattacherjee et al., 2007) and patient records (Dwivedi et al., 2007; Kirsch et al., 2007; Kharrazi et al., 2012). However, MHS have been known to fail. Lyytinen and Hirschheim (1987) argue that infrequent, inappropriate and ineffective long-term use of IS often contributes to failure. Lippert and Davis (2006) suggest that 50% of IT systems may be considered failures or fail to meet expectations. Failure to deliver on these expectations is often depicted in existing literature through abandonment or lack of use post-adoption (Hecks, 2006) of the technology implemented. One such study, conducted by Tang and Carpendale (2008) revealed their participants either completely abandoned or tried to avoid using the MHS post-adoption. Similarly, Standing and Standing (2008) found nurses abandoning the MHS when faced with certain barriers (i.e. most tended to revert to previous methods rather than persevere with the new system). In outlined studies the MHS was abandoned post-adoption. It is therefore important to investigate post-adoption use of any technological innovation to fully appreciate long term success of IT technologies (Stafford et al., 2010).

1.1 Post-Adoption Use of IT: Infusion

According to Saeed and Abdinnour-Helm (2008), understanding post-adoption use of any technological innovation, in this case, MHS, can provide insights on factors that can be leveraged by individuals to promote effective use of information systems after its initial acceptance. Extant research on post-adoption IT use however, has largely focused on continued use (Burton-Jones and Straub, 2006) and not on specific phases of post-adoption IT use (Shaw and Manwani, 2011). Various phases of post-adoption IT use exist including adaptation, acceptance, routinisation and infusion (Cooper and Zmud, 1990). Although a rich literature base exists on adoption, infusion remains one of the least studied facets of IT post adoption in the IS field (Ng and Kim, 2009; Tennant et al., 2011).

Infusion is commonly recognised as the last phase of the Cooper and Zmud (1990) stage model of IT implementation in organisations. Since its emergence in the IS literature in the mid-1980s, numerous definitions exist for IT infusion, often based on the level of analysis under investigation. The lack of consensus on a single, all-encompassing definition for what constitutes the term ‘infusion’ has resulted in a lack of clarity among scholars and inconsistent results. In deriving a definition of infusion numerous definitions were reviewed and a definition was established for this study which is “embedding IT within an individual’s work practice and utilising the IT to its full potential (i.e. usage of all possible and appropriate applications)”. 
In the context of this study, infusion is identified through highly exhaustive use of MHS within an individual’s daily activities. Highly exhaustive use occurs when clinicians use MHS in feature, integrative and exploratory ways. Feature use refers to the most basic use of MHS features to complete any given task (adapted from Oakley and Palvia, 2012). For example, using observation charts, laboratory reports, and entering patient data etc. Integrative use refers to the configuration of workflow linkages among a set of work tasks (Saga and Zmud, 1994). That is, using the content access through MHS to connect or ‘integrate’ various tasks to achieve an overall goal (adapted from Oakley and Palvia, 2012). Integrative use of MHS can be illustrated, for example, when clinicians prioritise which patients to see first. Finally, exploratory use captures active examination of new uses of the MHS by enabling users to find novel uses of the IS within their work environment (Abdinnour-Helm and Saeed, 2006). An example of exploratory use of MHS is checking for additional functionality outside of the mainstream mandatory functionality/features (e.g. Help functionality/various healthcare applications).

The remainder of this paper is structured as follows. A conceptual model of MHS infusion is presented in section 2 to address the gap in the literature relating to MHS infusion. This conceptual model, which draws upon and extends extant literature, is operationalised using a survey approach (section 3). Section 4 presents the empirical findings of the quantitative data analysis. Section 5 presents the key implications for theory and practice of this study and discusses the potential for future research within individual m-health infusion.

2 Conceptual Model for Understanding MHS Infusion

Infusion of mobile technologies in any industrial domain is under-investigated (O’Connor et al., 2012). Therefore, a conceptual model is derived for explaining MHS infusion by clinicians. This model consists of six factors (namely availability, self-efficacy, time-criticality, habit, technology trust and task behaviour) which impact infusion and three dependent variables including effectiveness, efficiency and learning (cf. Figure 1). All components of the model are measured reflectively as they adhere to the guidelines established by Jarvis et al., (2011). The eleven hypotheses for the infusion of MHS are outlined as follows:

Due to expenditure reasons, clinicians are often required to share IT (Daniel and Sabin, 2002). Availability is the ability of accessing mobile health system when required (O’Connor et al., 2012). Without the necessary resources (i.e. available MHS) staff cannot infuse the technology as they are always in use/demand. Therefore, it is hypothesised that:

\[ H1: \text{Availability of MHS impacts individual infusion of MHS.} \]

Self-efficacy refers to an individual's perceptions of his or her ability to use MHS in the accomplishment of a task (adapted from Compeau and Higgins, 1995). Infusing MHS requires clinicians to utilise the MHS in exhaustive ways (i.e. feature, integrative and exploratory use). The more self-efficacious individuals are with the MHS, the more confident they are with infusing the tool and become adept at discovering more efficient ways of using the MHS outside of their original use. However, not all highly self-efficacious individuals may infuse the MHS, Thus, it is hypothesised that:

\[ H2: \text{Self-Efficacy impacts individual infusion of MHS.} \]

Time-criticality represents the importance with which a task needs to be performed (Zhang et al., 2011). In this context, time-criticality refers to the willingness of healthcare practitioners to use MHS in urgent situations. In a healthcare environment, practitioners are often required to conduct tasks with a sense of urgency. It is therefore imperative that such staff can obtain patient content in a timely manner from the MHS. If MHS does not permit instant execution for a task then staff will not infuse the MHS. Therefore, it is hypothesised that:

\[ H3: \text{Time-Criticality impacts individual infusion of MHS.} \]
The longer the length of time clinicians interact with the MHS the more automatic their responses are for MHS infusion (Ng and Kim, 2012). Habit refers to the extent to which an individual automatically tends to use the MHS (adapted from Limayem et al., 2007). Clinicians who make it customary to use the MHS in exhaustive ways (i.e. feature, exploratory and integrative use) will embed the MHS within their daily work practices. Therefore, it is hypothesised that:

**H4: Habit impacts individual infusion of MHS.**

Technology trust refers to the degree to which an individual perceives that an MHS is capable of facilitating tasks based on expectation of technology functionality and reliability (adapted from McKnight et al., 2011). Delivering healthcare services to patients requires speedy access to patient information. It was therefore imperative that the MHS does not malfunction at the point-of-care and encompasses the necessary functions/features to allow speedy access to patient data and prevent information overload from occurring. Moreover, when the IT behaves reliably the users feel confident in their abilities to perform tasks (Oakley and Palvia, 2012). Individuals gain self-assurance about their capabilities to conduct work when the MHS have the necessary features/functions. Therefore, it is hypothesised that:

**H5: Clinicians’ perceived technology trust impacts self-efficacy.**

**H6: Clinicians’ perceived technology trust impacts time-criticality when delivering healthcare services.**

Task behaviour refers to the activities that team members perform using MHS to carry out a task (adapted from Chung and Guinan, 1994). Any patient being treated within a hospital environment is likely to be seen by multiple clinicians, all whom require access to their data to deliver healthcare services in a timely manner. Clinicians rely upon documentation concerning medical interventions or interactions with the patient from fellow colleagues to help inform decision making. Incomplete data from other colleagues impacts the timeliness of delivering healthcare services to patients as clinicians are required to locate that missing data. Moreover, all practitioners are required to retrieve and electronically record patient data which could be accessed through MHS at the point-of-care. Therefore, practitioners were required to frequently interact with staff and regularly use the information accessed through MHS. This inevitably could result in the habitual routines of automatic use of MHS at the point-of-care. Therefore, it is hypothesised that:

**H7: Task Behaviour among clinicians impacts time-criticality.**

**H8: Task Behaviour among clinicians impacts individual habitual routines.**

Embedding IT within individuals’ work practices was reported to improve individual performance (Jones et al., 2002). Firstly, performance is examined through effectiveness and efficiency. Effectiveness refers to the degree to which infusing MHS improves clinical care whereas efficiency refers to the degree to which infusing MHS leads to a more efficient workflow (O’Connor et al., 2011). Infusion of MHS enables clinicians to become more adept at discovering new uses of the MHS outside of their intended use. This can lead to better ways of delivering healthcare services by assisting clinicians with clinical decision making, reducing error rates and improving the monitoring and management of disease within hospital environments. Therefore, it is hypothesised that:

**H9: Infusion of MHS impacts individuals’ effectiveness in terms of clinical care.**

Moreover, MHS provide clinicians with clinical data/information independent of time and location. This ultimately saves time when delivering healthcare services as patient-related information is readily available to practitioners. Staff are not required to seek paper documents which could be stored offsite. However, exploratory use may be seen as a time-consuming activity. Therefore, it is hypothesised that:

**H10: Infusion of MHS impacts efficiency in terms of individuals’ work flow.**

Finally, infusion of MHS can enhance individual learning. Learning is the degree to which a clinician acquires an understanding of medical material accessed through MHS. MHS are a convenient source of information or means of communication that assist clinicians with medical learning. MHS are
portable devices which permit access to medical content independent of time and/or location. Therefore, it is hypothesised that:

\[ H11: \text{Infusion of MHS impacts individual learning.} \]

**Figure 1 Conceptual Model of MHS infusion**

### 3 Methodology

In operationalising the model (cf. Figure 1) an online survey instrument was designed using a web based survey administration tool (www.surveygizmo.com). Data obtained for this paper is part of a two phased sequential mixed methods appropriate and is based on qualitative data obtained earlier in the research process. As this research is exploratory in nature (little is known on MHS infusion at an individual level of analysis) a survey was the preferred data collection procedure as it allows for proposition/hypotheses testing and is considered a good technique for gathering base-line data for informing future research (Babbie, 2001). Data was gathered over a four month period from April 2012 to July 2012 from various clinicians in an acute care context within The Ottawa Hospital, Canada. The Ottawa Hospital currently has 3,000 iPads, incorporating a mobile Electronic Medical Record application, used daily by various clinicians.

A total of 157 responses were obtained via the administration on an online survey. After excluding 56 incomplete responses, 101 surveys were usable for data analysis. Due to the sample size the authors employed the Partial Least Square [PLS] (Structural Equation Modelling [SEM]) approach for data analysis purposes. This approach uses component-based estimations and allows simultaneous examination of both the measurement and the structural models. The measurement (outer) model portrays the relationships between a construct and its associated variables (measurement items) whereas the structural (inner) model represents direct and indirect unobservable relationships among constructs (Tenhaeus et al., 2005; Diamantopoulos 2006). SmartPLS (Version 2.0.M3) was utilised to generate the statistical outputs associated with the survey data.

### 4 Findings

This section presents the results of the quantitative analysis of the survey data. The robustness of the model is assessed through several reliability and validity tests (section 4.1). An assessment of the predictive or causal relationship between constructs in the model is presented in section (4.2).
4.1 Measurement Model Evaluation

Evaluating the measurement model requires an assessment of both reliability and validity. First, the reliability of construct measurements was evaluated by examining the average variance extracted and composite reliability. Average Variance Extracted (AVE) measures the amount of variance captured by the indicators in relation to the amount of variance due to measurement error (Fornell and Laraker, 1981) and should be equal to or exceed 0.5 (Chin, 1998). Composite Reliability (CR) refers to a measure of the internal consistency of indicators to the construct, depicting the degree to which they indicate the corresponding latent construct (Hair et al., 2006). All constructs exhibited composite reliability greater than the acceptable level of 0.6 (cut off point for exploratory purposes as depicted by Chin, 1998). The values for composite reliability are good, ranging between 0.76 and 0.93 (cf. Table 2). Furthermore, with respect to the data collected for this study, AVE scores for the measures exceeded the 0.5 threshold (cf. Table 1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>AVE</th>
<th>Composite Reliability</th>
<th>Variable</th>
<th>AVE</th>
<th>Composite Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability</td>
<td>0.682994</td>
<td>0.865864</td>
<td>Infusion*</td>
<td>0.665271</td>
<td>0.863600</td>
</tr>
<tr>
<td>Effectiveness</td>
<td>0.676838</td>
<td>0.893136</td>
<td>Integrative</td>
<td>0.609559</td>
<td>0.823588</td>
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<tr>
<td>Efficiency</td>
<td>0.585988</td>
<td>0.847876</td>
<td>Learning</td>
<td>0.681992</td>
<td>0.863968</td>
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<td>0.867588</td>
<td>Reliability</td>
<td>0.799689</td>
<td>0.922894</td>
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<tr>
<td>Feature</td>
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<td>0.857844</td>
<td>MHS Self-Efficacy</td>
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<td>0.938575</td>
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<td>0.762646</td>
<td>0.905905</td>
<td>Task Behaviour</td>
<td>0.519038</td>
<td>0.763298</td>
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<td>0.936728</td>
<td>Technology Trust*</td>
<td>0.822685</td>
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<td>Time-Criticality</td>
<td>0.680201</td>
<td>0.864272</td>
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</table>

Table I  Internal Consistency Reliability Test

When computing the AVE and CR for higher order Latent Variables (LV) SmartPLS uses the loadings of the repeated indicators and not the loading from the second order LV to its first order LV (these loadings are reported as path coefficients). Therefore, in order to calculate AVE and CR for second-order constructs (marked with * in Table 2), the recommended calculations as suggested by Fornell and Larcker (1981) and Tenenhaus et al., (2005) were followed.

Second, individual reliability of indicators was assessed. The value of 0.6 is used as the threshold cut-off point for examining individual reliability (Hair et al., 2006). The threshold of 0.6 was selected as (1) this research study is exploratory in nature. The objective of exploratory research is to gather preliminary information that will help define problems and explore hypotheses. Therefore, this research does not seek to confirm the findings but provides for a better understanding of infusion of mobile technologies in a healthcare domain; (2) the conceptual model consists of reflective constructs. Here the emphasis is placed on the construct rather than the individual indicators. The underlying rationale for this is that the indicators do not cause the construct but in fact are manifestations of the construct (Jarvis et al., 2011). As a result, it is imperative that the emphasis is placed on construct reliability.

Table 2 depicts that all indicators are higher than the acceptable level of 0.60. For second-order constructs reliability is assessed by examining the path coefficients between the second order latent variable to its first order latent variable (Fornell and Larcker, 1981; Tenenhaus et al., 2005). However, these items were higher than the acceptable level of 0.60 and will be retained because this study is exploratory in nature (Hair et al., 2006). For second-order constructs reliability is assessed by examining the path coefficients between the second order latent variable to its first order latent variable (Fornell and Larcker, 1981; Tenenhaus et al., 2005).
Next, convergent and discriminant validity are used to assess correlations within and between constructs respectively (Terenhaus et al., 2005). In the case of convergent validity, the values of the average variance extracted (AVE) were observed, as proposed by Fornell and Larcker (1981). Table 1 highlight that AVE exceeds 0.5, which indicates sufficient convergent validity (each latent variable explains more than 50% of their indicator variance on average).

### Table 2  Item Loading Values

<table>
<thead>
<tr>
<th>Latent Variable</th>
<th>Item</th>
<th>β</th>
<th>Latent Variable</th>
<th>Item</th>
<th>β</th>
<th>Latent Variable</th>
<th>Item</th>
<th>β</th>
</tr>
</thead>
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<td>Technology Trust*</td>
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<td>0.913</td>
<td>Time-Criticality</td>
<td>TC1</td>
<td>0.884</td>
<td>Exploratory Use</td>
<td>InfExp1</td>
<td>0.816</td>
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<tr>
<td></td>
<td>Functionality</td>
<td>0.901</td>
<td></td>
<td>TC2</td>
<td>0.834</td>
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<td>InfExp2</td>
<td>0.829</td>
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<tr>
<td>Reliability</td>
<td>TTRel1</td>
<td>0.901</td>
<td></td>
<td>TC3</td>
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<td>InfExp3</td>
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<td></td>
<td>TTRel2</td>
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<td>Habit</td>
<td>Hab1</td>
<td>0.914</td>
<td>Effectiveness</td>
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<td></td>
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<td>Effect2</td>
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<td>Infusion*</td>
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<td></td>
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<td>Feature Use</td>
<td>InfExp2</td>
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<td>Integrative Use</td>
<td>InfExp3</td>
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<td>Task Behaviour</td>
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<td></td>
<td>Exp. Use</td>
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<td></td>
<td>Effic1</td>
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<td></td>
<td>TB2</td>
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<td>Feature Use</td>
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<td>Effic3</td>
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<td>Availability</td>
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<td>Learning</td>
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<td>Avail2</td>
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<td>InfFeat4</td>
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<td></td>
<td>Avail3</td>
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<td>Integrative Use</td>
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<td>Self-Efficacy</td>
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<td>SE2</td>
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<td>InfInt2</td>
<td>0.761</td>
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<td>0.691</td>
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<tr>
<td></td>
<td>SE3</td>
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<td>InfInt3</td>
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<td>Learn3</td>
<td>0.860</td>
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</table>

### Table 3  Cross-Construct Matrix

| A=Availability, B=Effectiveness, C=Efficiency, D=Exploratory Use, E=Feature Use, F=Functionality, G=Habit, H= Infusion, I=Integrative Use, J=Learn, k= Reliability, L=MHS Self-Efficacy, M= Task Behaviour, N= Technology Trust, O = Time-Criticality |

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
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<th>L</th>
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<tr>
<td>0.68</td>
<td>0.68</td>
<td>0.59</td>
<td>0.69</td>
<td>0.67</td>
<td>0.8</td>
<td>0.8</td>
<td>0.7</td>
<td>0.61</td>
<td>0.7</td>
<td>0.78</td>
<td>0.84</td>
<td>0.52</td>
<td>0.82</td>
<td>0.86</td>
</tr>
</tbody>
</table>
Achieving *discriminant validity* requires that the AVE is larger than the squared correlation of this factor with any other factor in the model (Chin, 1998). Table 3 shows all constructs have sufficient discriminant validity. The loadings and cross-loadings of indicators were also assessed. Indicator loadings should correlate higher with its respective construct compared with other constructs in the model. In this study, indicators loaded higher in its own construct than any other construct. Results of these tests show that manifest variables (indicators) presented in the research model are reliable and valid.

### 4.2 Structural Model Evaluation

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>T Statistics</th>
<th>Significant (2-tailed)</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Availability of MHS impacts individual infusion of MHS.</td>
<td>2.774709</td>
<td>p&lt;0.01</td>
<td>Supported</td>
</tr>
<tr>
<td>H2: Self-Efficacy impacts individual infusion of MHS.</td>
<td>2.366600</td>
<td>p &lt; 0.05</td>
<td>Supported</td>
</tr>
<tr>
<td>H3: Time-Criticality impacts individual infusion of MHS.</td>
<td>4.291736</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H4: Habit impacts individual infusion of MHS.</td>
<td>2.683276</td>
<td>p &lt; 0.01</td>
<td>Supported</td>
</tr>
<tr>
<td>H5: Clinicians’ perceived technology trust impacts self-efficacy.</td>
<td>5.942945</td>
<td>p&lt;0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H6: Clinicians’ perceived technology trust impacts time-criticality when delivering healthcare services.</td>
<td>1.359702</td>
<td>p&lt;0.1</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H7: Task Behaviour among clinicians impacts time-criticality.</td>
<td>8.345848</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H8: Task Behaviour among clinicians impacts individual habitual routines.</td>
<td>5.139563</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H9: Infusion of MHS impacts individuals’ effectiveness in terms of clinical care.</td>
<td>11.475577</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H10: Infusion of MHS impacts efficiency in terms of individuals’ work flow.</td>
<td>12.562744</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
<tr>
<td>H11: Infusion of MHS impacts individuals’ learning.</td>
<td>8.896167</td>
<td>p &lt; 0.001</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Table 4  Hypotheses testing outcomes

Analysis of the structural model allows us to accept or reject each hypothesis as well as understand the actual contribution that an independent variable makes in explaining the variance in a dependent variable (Vinzi et al., 2010). The eleven hypotheses were tested (i.e. examining strength and significance) by employing the bootstrapping re-sampling technique to calculate the corresponding t-values for each path, in order to assess the significance of path estimates. Since larger numbers of resamples lead to more reasonable estimates of standard error (Tenenhaus et al., 2005) the bootstrapping procedure was undertaken using 101 cases with 1000 samples to produce stable results. The path coefficients are presented in Figure 2 and the outcomes of the hypotheses (i.e. supported or not) are depicted in Table 4.

Time-criticality was significantly found to directly impact MHS infusion. The weakest association (in terms of significance) in the model was found between technology trust and time-criticality. Significant associations were found between infusion and all three individual-level outcomes. The most significant relationship was found between infusion and effectiveness indicating that clinical care to patients improves as infusion of MHS increases by clinicians.

### 5 Discussion and Conclusions

By exploring MHS infusion, this paper makes a number of significant theoretical and practical contributions of value to both the academic and practitioner communities.
5.1 Contribution to Theory

This study first contributes to the e-health domain. If healthcare organisations want to overcome issues of abandonment or lack of post-adoptive use of mobile technological artefacts and appreciate the potential of mobile technology for clinicians (i.e. improvements in clinical care, work practices and learning) then a clearer understanding of MHS infusion must be achieved. This paper begins to address this gap in extant literature by presenting a conceptual model of individual MHS infusion. This model not only identifies the factors which impacts MHS infusion but also the benefits clinicians gain from embedding same within their work practices. In deriving the conceptual model a number of theories used in the IS domain were investigated (e.g. task, technology, user fit; success model, diffusion of innovations). This signifies that theories outside of the mainstream medical domain can be utilised to fully understand e-health initiatives. This study documents that time-criticality has the strongest direct association with the infusion of MHS. The concept of urgency is not new to the e-health domain. However, this finding is of theoretical value as it suggests that the perceptions of clinicians regarding the infusion of MHS appears to be influenced more by task characteristics (i.e. time-criticality) than user and technology characteristics. In the context of this study, clinicians are most concerned with accessing and utilising patient-related information on demand. This is of theoretical value as clinicians are concerned with both the system and content quality offered by MHS even at post-adoptive phases of implementation. Through empirical investigation, this study presents evidence of a positive association between infusion and individual performance (in terms of effectiveness and efficiency) and learning. Theoretically, this is significant as it illustrates that when clinicians embed MHS within their daily work practices, clinicians are mindful of the value they can obtain from such technological artefacts.

This study further contributes to existing knowledge in the infusion domain. It answers a call for research by Oakley and Palvia (2012) to investigate mobile infusion at an individual level of analysis. Therefore, it extends the limited knowledge on mobile infusion. In doing so, researchers now have a better understanding of how mobile technological artefacts are embedded within individuals’ work practices. As outlined previously time-criticality impacts MHS infusion. Theoretically, this is significant to the infusion literature, as it illustrates an important factor which impacts infusion which was previously unreported in the infusion domain. Moreover, previous research (Pongpattrachai et al., 2009) noted that the availability of resources, such as time and finance, is imperative for IT infusion. This research study extends this concept by illustrating that the availability of mobile technological artefacts (i.e. MHS) positively impacts upon individual infusion. This is also of theoretical value, as it suggests that individuals/organisations may be required to invest heavily in technological tools to ensure that they can be fully embedded within work practices. Previous research noted that self-efficacy plays an important role in the literature pertaining to IT infusion (Vannatta et al., 2001; Pongpattrachai et al., 2009). This study corroborates existing research in the infusion domain but also extends research on this concept by illustrating that self-efficacy impacts MHS infusion at an individual level of analysis. It lends empirical support to the work of Oakley and Palvia (2012) who argued that mobile device self-efficacy positively impacts infusion. This offers a contribution to theory as it signifies that on-going training is paramount for infusion. It is often documented that training ceases after the technology has been adopted. Yet, as time passes, users should still receive training frequently post-adoption to ensure they are aware of any new features/functionalities offered by the technological artefact. Similarly, the concept of habit has previously been explored in the infusion domain and was found to impact infusion (Mäkinen and Jaakkola, 2000). In the context of this study, clinicians adopted ‘good’ habitual routines which enabled them to embed the MHS within their daily work practices. Dependent upon the user and technological artefact utilised, individuals could become accustomed to their current usage and not fully embed the technology within their daily work practices. Moreover, healthcare practitioners are reported to be resistant to change. Therefore, instead of enforcing change on clinicians, they should be encouraged to employ ‘good’ habitual routines from early phases of IT implementation.

This research significantly contributes to the infusion domain by examining outcomes from infusing technological artefacts. Research examining individual outcomes is scarce not only in the mobile
infusion literature but also in the generic IT infusion literature. The results of this study reveal that the infusion of MHS by clinicians has a positive impact on individual-level outcomes such as effectiveness, efficiency and learning. The impact of infusion on learning was previously reported in one infusion based study by White et al., (2005). This study coincides with their work and argues that learning improves as a result of infusing MHS in a healthcare domain. This study extends the work of White et al., (2005), however, by quantifying the extent to which infusion of MHS by clinicians impacts learning. Existing research examining the impact MHS infusion on individual effectiveness is under investigated in the infusion literature. White et al., (2005) found that MHS infusion can lead to improvements in terms of delivering healthcare services. This study reinforces this fact; but yet goes further by concluding that effectiveness is the factor impacted the most by MHS infusion by clinicians. Finally, infusion was also found to positively impact efficiency. It corroborates the work of Basole (2004) by arguing that mobile technological tools result in high levels of workflow efficiency, but goes further by investigating workflow efficiencies in a healthcare domain by clinicians through the infusion of MHS.

Finally, this study contributions to the generic IS literature as it moves beyond the narrow focus of examining use (e.g. frequency of use) and continued use of technological artefacts to understanding broader ways in which IS can be embedded within individuals work practices (e.g. feature use, integrative use and exploratory use). It further extends the body of knowledge pertaining to post-adoption of technological artefacts.

5.2 Contribution to Practice

Organisations invest heavily in MHS (McKinsey, 2010), whether it is initiated to gain benefits or competitive advantage or to increase performance of individual users utilising the technology. Yet despite existing research on e-Health, some investment initiatives fail to achieve such benefits. For MHS to be truly valuable to organisations and individuals, it must be infused within the individual’s work practices. As established in this study, infusion of MHS improves the delivery of healthcare services to patients at the point-of-care and individuals workflow by reducing the time necessary to conduct tasks. Moreover, findings reveal that learning was enhanced when infusion of MHS increased. This study therefore has significant implications for organisations looking to invest in MHS and for those seeking to understand how a practitioner’s performance can be improved through infusion. The findings of the study present evidence of a direct, positive association between availability, self-efficacy, time-criticality, habit and infusion respectively. Moreover, technology trust and task behaviour was found to indirectly impact infusion. Without sufficient resources staff will not have the available MHS to infuse the technology. Moreover, it is imperative that healthcare organisations/managerial staff promote training initially so individual users become aware of existing features/functionality therefore establishing habitual routines and improving confidence in one’s own ability to complete tasks and reach goals. To ensure that MHS are infused by clinicians there must be a collaborative environment for users to interact and share clinical data/information with fellow colleagues. Moreover, both medical and technical staff should collaborate towards improving the existing MHS. This is often achieved through exploratory use of MHS; thus, practitioners should have a safe domain in which to explore the MHS. For software developers (or in-house developers) who wish to develop a mobile healthcare application, the implications of the findings from this study are that a key step towards the infusion of such an application is to ensure that information can be received, with no delays, on demand. Furthermore, it is imperative that the MHS (1) operates safely and does not malfunction and (2) that the application is dynamic in nature and evolves to meet the needs of the individual user overtime. This study has potentially significant implications for both theory and practice. However, the hypotheses are examined from the analysis of data from a single-case study. As with all single-case study research the conclusions and findings arrived at in this study may not be generalisable. Further research is now required to investigate this conceptual model in other industrial domains to provide for a better understanding of mobile artefacts by individual users.
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