Abstract

Mobile payments (m-payments) appear to have the potential to be among the more popular of mobile services, however, take-up has been lower than anticipated, and given associated levels of investment, the issue is of strategic organizational concern. This paper presents a study investigating consumer intentions toward m-payments, extending existing knowledge by developing and evaluating a model that incorporates factors relevant to the m-payment context, including a multi-dimensional treatment of perceived risk. Empirical data to test the model were captured in a region expected to exhibit strong mobile data traffic growth, and were analyzed using variance-based structural equation modeling. The empirical application of the model augments knowledge at the human level of the formation of consumer intentions to use m-payments. The authors also suggest a contribution from an organizational and managerial perspective through presenting information that has implications for development, management, and marketing of m-payment services.

Keywords
Mobile Payments, Technology Adoption, Multi-Dimensional Risk, PLS, Moderators

Introduction

Developments in mobile technologies such as smart mobile phones and tablets have resulted in the mobile platform emerging as a key tool with which to engage consumers (Gao et al. 2013). Mobile payment services (m-payments) provide consumers with an anywhere, anytime ability to conduct financial transactions over mobile or wireless networks via the use of a mobile device (Chandra et al. 2010). However, despite the apparent potential of the technology, and the fact that m-payments are gaining traction globally, actual take-up has been lower than anticipated with for instance, 52% of North Americans being “extremely aware” of m-payments but only 18% using them on a regular basis (Silbert 2015), leading to the question of why consumers have not been adopting m-payments to expected levels.

Differences between predicted and actual adoption levels suggest there is a need for greater understanding of what motivates consumers to make use of mobile payment services, and as understanding of human and organizational, aspects of technological investments are key to the success of those investments (Irani et al. 2015), the shortfall between predicted and actual adoption of m-payments suggests that current organizational standpoints may be misaligned with consumer perspectives, and that there remains a need for greater understanding in this respect; specifically, greater awareness of what motivates consumers to make use of m-payments, or prevents them from doing so, in order that the technology may be managed and promoted effectively.

Against this backdrop, and given the organizational and managerial relevance, along with the need to reduce the gap between awareness and adoption, the aim of this paper is to present details of an empirical investigation into human factors influencing consumer adoption of m-payments, thus contributing to the body of knowledge in this area. The study combines core components of Davis’ (1989) Technology Acceptance Model (TAM) with constructs which have attracted substantial attention from researchers investigating consumer perceptions of innovations, and which are
appropriate within the context of m-payments (Dahlberg et al. 2015); perceived risk, trust, which has long been associated with risk (Vincent-Wayne 1999), and compatibility. Moreover, in keeping with research perceiving risk as being multi-dimensional (Luo et al. 2010), risk is modeled as a multi-dimensional construct in this study.

The article makes both theoretical and managerial contributions. From a conceptual perspective, it extends existing knowledge by developing a technology acceptance model that incorporates factors relevant to the m-payment context; the empirical application of the model augmenting knowledge of the formation of consumers’ intentions to use m-payments. From a managerial perspective, it presents information that has implications for those responsible for promoting m-payment services. Insights into the relevance of factors influencing the adoption decision provide greater understanding of how m-payments could be marketed more effectively, leading to increased acceptance.

The paper is organized as follows. The next section provides an overview of the theoretical context, the development of the proposed model and hypotheses tested. This is followed by an account of the methods employed, and by sections presenting and discussing the results. Finally, concluding remarks including theoretical and practical implications, limitations, and suggestions for further research are presented.

Conceptual Framework and Hypotheses

**Theoretical Basis**

Consumer acceptance of innovations has long been a subject of interest for both researchers and practitioners, and remains a management challenge (Williams et al. 2009). In the case of m-payments, consumer-focused studies have employed a range of theories, including Diffusion of Innovation (DoI) Theory, the Information Systems Success Model, and the Unified Theory of Acceptance and Use of Technology, although TAM is the most often used as a theoretical base for consumer-focused studies (Dahlberg et al. 2015), with additional constructs being incorporated specifically for the study of m-payments. TAM suggests that acceptance of technology at the individual level is predicated upon two key variables; perceived ease of use (PEOU), and perceived usefulness (PU), and that these, in turn, predict attitudes toward that technology, along with subsequent use.

Previous studies have provided extensive empirical evidence supporting the relationships between TAM constructs (Choi and Totten 2012), hence TAM was viewed as providing an appropriate theoretical core for use in this study, predicting that an individual’s intention to use m-payments depends on his or her perceptions of PU and of PEOU of m-payments. Furthermore, PEOU will have a positive effect on the PU of m-payments. Specifically, the following are hypothesized:

H1. Perceived usefulness positively affects user intention to use m-payments.
H2. Perceived ease of use positively affects user intention to use m-payments.
H3. Perceived ease of use positively affects perceived usefulness of m-payments.

**Trust**

The concept of trust has long been seen to have significant impact on consumer behavior, with many definitions and conceptualizations presented (Colquitt et al. 2007). This study adopts the perspective of the much cited work of Rousseau et al. (1998), who refer to trust as a willingness to be vulnerable to actions based on an expectation that the other party will engage in acceptable practices, and, as a psychological state comprising the intention to accept vulnerability based on positive expectations. Both explanations comprise two primary components; intention to accept vulnerability, and positive expectations (Colquitt et al. 2007). Unsurprisingly, the concept is viewed as being highly important in the context of intention to use new technologies (Chong 2013) with, for instance, lack of trust being frequently cited as a reason why consumers do not make on-line purchases (Glover and Benbasat 2011). The concept is therefore also likely to be significant in the context of m-payments, in which there is a clear relinquishing of control (accepting vulnerability) based on the belief that the anticipated service (correct payment) will be provided (positive expectation).

Moreover, trust has long been associated with perceived risk (Vincent-Wayne 1999), the concepts being modeled together in numerous studies of on-line activity, with both being found to influence consumer attitudes (Glover and Benbasat 2011). Trust is generally modeled as influencing perceived risk on the basis that greater levels of trust are expected to lower levels of perceived risk, and thus,
consumers' perceived risk regarding use of m-payments would be expected to decrease as trust in m-payments increases, hence:

H4. Trust has a positive effect on users’ intention to adopt m-payments.
H5. Trust has a negative effect on perceived risk of using m-payments.

**Perceived Risk**

Perceived risk is viewed as arising from unanticipated consequences of an undesirable nature resulting from product purchase, and has long been the focus of research attempting to better understand consumer behavior (Forsythe and Shi 2003). Following the seminal works of Cunningham (1967) and of Kaplan et al. (1974), which distinguish between different categories of risk, a stream of literature appeared supporting the multi-dimensional nature of the risk construct (Luo et al. 2010), including those examining intentions to use new technology such as e-services (Featherman and Pavlou 2003) and m-banking (Luo et al. 2010). Thus the view of risk as being multi-dimensional in nature is viewed as being an appropriate approach for this study; specifically we employ a variation of the tactic used by Featherman and Pavlou (2003) in replacing the physical (safety) concept with privacy risk, which is more appropriate in the context of m-payments given that there is no obvious physical hazard in the activity. Therefore the dimensions of risk employed in this study are; financial (using m-payments could result in financial loss); performance (m-payments may fail to perform as expected); privacy (using m-payments could result in the loss of personal information); psychological (using m-payments could lower self-image or esteem); social (using m-payments could result in loss of status or looking foolish); time (using m-payments could result in loss of time by having to correct errors). In keeping with previous work investigating consumers’ intentions toward new technologies, consumers’ intentions to adopt m-payments would be expected to decrease as risk perceptions increase, hence it is hypothesized:

H6: Perceived risk has a negative effect on users’ intention to adopt m-payments.

**Compatibility**

Compatibility is the degree to which an innovation is perceived to be consistent with potential users’ existing values, past experiences, and current needs (Rogers 2003). Compatibility has previously been identified as being a useful extension of TAM (Schierz et al. 2010), with numerous studies having investigated the relationships between compatibility and TAM variables in the context of mobile technologies, including those by Aldás-Manzano et al. (2009) on m-shopping, and Wu and Wang (2005) on m-commerce. In the m-payment context, compatibility has been previously identified by Dahlberg et al. (2015) as being a highly relevant construct, and hence would be expected to positively impact upon the perceived usefulness, perceived ease of use, and intention to adopt m-payments.

Rogers (2003) explains how more compatibility results in less uncertainty, which in the context of technology acceptance, can be interpreted as resulting in less potential for risk (reduced uncertainty suggesting less concern for unanticipated consequences). Furthermore, Rogers’ view that greater compatibility allows an individual to imbue an innovation with greater meaning and hence greater familiarity, suggests that compatibility also has positive influence on levels of trust, and correspondingly, a negative influence on levels of risk. Hence the following are hypothesized:

H7: Compatibility has a positive effect on perceived usefulness of m-payments.
H8: Compatibility has a positive effect on perceived ease of use of m-payments.
H9: Compatibility has a positive effect on user’s trust.
H10: Compatibility has a negative effect on user’s perceived risk.
H11: Compatibility has a positive effect on users’ intention to adopt m-payments.

**Methodology**

**Subjects and Data Collection**

The majority of studies investigating consumers’ acceptance of technologies have focused on industrialized countries (Alsajjan and Dennis 2010), and while additional research in general is needed on aspects of consumer adoption of m-payments (Dahlberg et al. 2015), regional and national variations in studies continue to support the view that research is required in diverse cultural settings as consumer responses to technology may differ across cultures. Consequently, data for this study
were collected in a developing country within the Middle East and Africa block - an area currently exhibiting the strongest mobile data traffic growth (Cisco 2016), and hence one with much potential for m-payment use. Participants in the study were professionals employed in the financial, health, and technology sectors, who were regular mobile phone users, and hence were viewed as being likely to have both the opportunity and skills required to make use of m-payment services, and were potential users of m-payments. Hence, this is an instance of a pre-usage study as discussed by Montazemi and Qahri-Saremi (2015).

In keeping with previous work on technology acceptance (Williams et al. 2009), a survey methodology employing a questionnaire was used in this study. Initial questions were derived from a literature review. The resulting questionnaire was then pre-tested by an expert panel comprising doctoral candidates and faculty members. Revisions regarding structure and wording were made at this point. A pre-test with a convenience sample of eight consumers was conducted in order to confirm clarity and ensure unambiguous communication, and following consideration of feedback obtained during this process, further minor changes were made to the wording of some of the questions. The final version of the questionnaire was distributed with the request that original participants provide details of contacts in different firms, thus increasing the reach of the study. This snowball-sampling approach is often used where the target population may be difficult to locate and enumerate (Faugier and Sargeant 1997); m-payments being largely an emerging technology in the region, there is no reliable sampling frame of potential users. This process resulted in questionnaires being distributed to 300 professionals, with 265 participants responding. Of the questionnaires returned, 28 were incomplete, leaving 237 usable responses. Responses were received from 154 males and 83 females, 76.6% of males being between the ages of 18-35, 20.8% between 36-50, and 2.6% being over 50; the corresponding figures for females being 83%, 13.5%, and 3.5% respectively. All respondents were regular mobile phone users, with 62.9% being contract-based and 37.1% using non-contractual arrangements. Respondents owned smart phones in 85.7% of cases, with 14.3% using basic handsets; 91.1% reported using mobile phones to access m-services such as email or browsing the web.

**Measurement**

Items used to measure the original TAM constructs, and the added constructs of compatibility, trust, and dimensions of risk were drawn from previously validated scales in the extant literature relating to m-banking/m-payments where possible, being reworded where appropriate to fit the context of this study. All items used a seven-point Likert scale, anchored from 'strongly disagree' to 'strongly agree'. The future tense of verbs was used for all items based on the understanding that all respondents were potential, and not existing, users. Items used to measure PU, PEOU, intention to use, and compatibility were adapted from the m-payments study of Schierz et al. (2010). Items to capture trust were adopted from Kim et al. (2008), with the various dimensions of perceived risk (financial, performance, psychological, social, time, and privacy) being captured using items adapted from Featherman and Pavlou (2003).

**Analysis and Results**

Data analysis was performed using Partial Least Squares (PLS), a variance-based structural equation modelling (SEM) approach allowing simultaneous analysis of both measurement model and structural model.

**Risk as a Higher-Order Component**

Multi-dimensional constructs can be modeled in a number of ways, this study employing the two-stage approach similar to that of Henseler and Chin (2010) in which a repeated indicator approach is used to obtain latent variable scores for the first-order components, which in turn serve as manifest variables in the second-order component measurement model.

Measurement quality of the formative higher-order component was tested as recommended by Diamantopoulos and Winklhofer (2001). Examination of the correlations between the first-order perceived risks varied from 0.16 to 0.59, the average being 0.37. This confirms that perceived risk is better represented as a formative higher-order component, as according to Pavlou and El Sawy (2006), a reflective higher-order construct would show particularly high correlations among its first-order factors (often above 0.8). In terms of relationships between perceived risk and its first-order constructs, all path coefficients from first-order constructs to the second-order construct were significant at the 1% level and were above or near .20 (Financial – 0.20; Performance – 0.15;...
Psychological – 0.29; Social – 0.28; Time – 0.33; Personal – 0.17), thereby indicating that risk performs well as a second-order construct.

The variance inflation factor (VIF) was calculated for first-order risk constructs to assess multicollinearity. VIF values above 10 suggest the existence of excessive multicollinearity and raise doubts about the validity of the formative structure (Diamantopoulos and Winklhofer 2001). In this study, VIF values ranged from 1.0 to 4.6 and tolerance from 0.214 to 0.992 for the six first-order factors, being within commonly acceptable thresholds of below 10 (VIF) and above 0.1 (tolerance) (Henseler et al. 2009), and also satisfying the more stringent values suggested by Hair et al. (2012) for PLS-SEM analysis, of VIF below 5 and tolerance above 0.2, suggesting that multicollinearity was not a concern.

**Measurement Model Evaluation**

All first-order constructs in the research model are reflective, measurement quality being verified by examining convergent validity, discriminant validity, and internal consistency. The influence of common methods bias was also studied. Summary results for measurement model quality are provided in Table 1.

Convergent validity was assessed in two ways. Firstly, item reliability was examined for each item. All indicators had loadings well above 0.6, apart from two - one measuring performance risk and one measuring intention to use. Neither exceeded 0.5, and hence were removed from the model. Remaining item loadings exhibited adequate convergent validity and were retained for subsequent analysis. Secondly, average variance extracted (AVE) was examined for each construct. All AVE values were substantially greater than the 0.5 threshold, thus indicating satisfactory reliability and convergent validity.

Discriminant validity (the extent to which a particular construct differs from other constructs) was also assessed in two ways. Firstly, all items loaded well onto their corresponding constructs, and more heavily than onto other constructs. Secondly, the square root of AVE for each factor was higher than the correlations with all other factors (see Table 2), indicating that each factor shares higher variance with items in its own factor than with items in other factors, again satisfying conditions for discriminant validity.

Internal consistency was assessed by means of composite reliability measures (CR), all of which were greater than the 0.7 threshold. Internal consistency was further assessed via Cronbach’s α values, all of which were above 0.7, indicating either excellent (0.90 and above) or high (0.70-0.89) reliability.

<table>
<thead>
<tr>
<th>Latent Variable</th>
<th>Composite Reliability</th>
<th>Cronbach’s α</th>
<th>AVE</th>
<th>Convergent/Discriminant Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compat</td>
<td>0.9145</td>
<td>0.8586</td>
<td>0.7818</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Financial Risk</td>
<td>0.8909</td>
<td>0.8171</td>
<td>0.7314</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Behav Intent</td>
<td>0.9483</td>
<td>0.9183</td>
<td>0.8595</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>PEOU</td>
<td>0.9491</td>
<td>0.9195</td>
<td>0.8614</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>PU</td>
<td>0.9462</td>
<td>0.9242</td>
<td>0.8147</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Perf Risk</td>
<td>0.8690</td>
<td>0.7116</td>
<td>0.7690</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Privacy Risk</td>
<td>0.8866</td>
<td>0.7461</td>
<td>0.7964</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Psychol Risk</td>
<td>0.8790</td>
<td>0.7925</td>
<td>0.7084</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Social Risk</td>
<td>0.9193</td>
<td>0.8689</td>
<td>0.7916</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Time Risk</td>
<td>0.9170</td>
<td>0.8644</td>
<td>0.7865</td>
<td>Yes / Yes</td>
</tr>
<tr>
<td>Trust</td>
<td>0.9154</td>
<td>0.8629</td>
<td>0.7829</td>
<td>Yes / Yes</td>
</tr>
</tbody>
</table>

**Table 1. Summary Results for Measurement Model Quality**

Common methods bias (CMB) can be a major source of measurement error for survey-based research, and given that high CMB may lead to incorrect conclusions being reached about relationships between constructs, Harman’s single-factor test was used to check if a single common factor accounted for the majority of variance across all factors. Harman’s test yielded nine factors with Eigenvalues above one, the first factor accounting for 26.8% of variance and all five factors accounting in total for 77.3% of total variance, suggesting that CMB was not present in the data. Given that the absence of a single factor accounting for the majority of variance does not fully eliminate the possibility of CMB...
Antecedents of Mobile Payment Adoption

(Podsakoff et al. 2003), and the acknowledged inability of Harman’s test to detect moderate to small levels of CMB (Craighead et al. 2011), the test employed by Pavlou et al. (2007) was performed, in which the construct correlation matrix is examined to determine if any constructs correlate exceptionally highly (> 0.90). No such correlations were present, providing further support that CMB was not an issue.

Results from evaluation of the measurement model therefore demonstrated the adequate convergent and discriminant validity, internal consistency, and absence of CMB necessary to justify testing of the hypotheses.

<table>
<thead>
<tr>
<th>Comp</th>
<th>Finan</th>
<th>Intent</th>
<th>PEOU</th>
<th>PU</th>
<th>Perf</th>
<th>Priv</th>
<th>Psych</th>
<th>Social</th>
<th>Time</th>
<th>Trust</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comp</td>
<td>0.8842</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Finan</td>
<td>0.0704</td>
<td>0.8552</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intent</td>
<td>0.6651</td>
<td>0.0986</td>
<td>0.9271</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PEOU</td>
<td>0.4084</td>
<td>-0.0123</td>
<td>0.411</td>
<td>0.9281</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>0.5653</td>
<td>0.0475</td>
<td>0.6042</td>
<td>0.5273</td>
<td>0.9026</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perf</td>
<td>0.1229</td>
<td>0.4483</td>
<td>0.0941</td>
<td>-0.0414</td>
<td>0.0194</td>
<td>0.8769</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priv</td>
<td>0.2376</td>
<td>0.365</td>
<td>0.1367</td>
<td>0.0737</td>
<td>0.0438</td>
<td>0.4458</td>
<td>0.8924</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psych</td>
<td>0.2605</td>
<td>0.2386</td>
<td>0.1547</td>
<td>0.2173</td>
<td>0.1843</td>
<td>0.3097</td>
<td>0.4253</td>
<td>0.8417</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social</td>
<td>0.0069</td>
<td>0.161</td>
<td>-0.0133</td>
<td>0.1213</td>
<td>-0.0431</td>
<td>0.234</td>
<td>0.2175</td>
<td>0.5971</td>
<td>0.8897</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>0.3753</td>
<td>0.2988</td>
<td>0.1626</td>
<td>0.2641</td>
<td>0.1929</td>
<td>0.4159</td>
<td>0.4117</td>
<td>0.5533</td>
<td>0.5027</td>
<td>0.8868</td>
</tr>
<tr>
<td>Trust</td>
<td>0.3746</td>
<td>0.1083</td>
<td>0.3751</td>
<td>0.4316</td>
<td>0.3782</td>
<td>0.0184</td>
<td>0.0506</td>
<td>0.0494</td>
<td>-0.0748</td>
<td>0.0795</td>
</tr>
</tbody>
</table>

Table 2. First-Order Construct Correlation Matrix - Square root of AVE on the diagonal

Structural Model Evaluation

Results of hypothesis testing are summarized in Table 3. R² values for each endogenous variable explain 42.5% of the variance in PU, 16.7% of the variance in PEOU, 14% of the variance in trust, 22.5% of the variance in perceived risk, and 53.3% of the variance in intention to use m-payments.

Calculation of the Stone-Geisser criterion returned Q² values of 0.35 (PU), 0.14 (PEOU), 0.11 (trust), 0.37 (perceived risk), and 0.42 (intention to use), underlining the model’s predictive relevance. Power analysis returned a value substantially above the 0.8 threshold of Cohen (1988), further underpinning confidence in the findings. Bootstrapping was performed to compute t-statistics and obtain significance levels for each of the hypothesized relationships – parameter settings for bootstrapping include 237 cases per sample, no sign changes, and 5,000 samples.

Moderator Analysis

Multi-group analysis based on gender as a moderator did not reveal any significant differences between R² values obtained at the 5% level; however, there was some evidence of difference between R² values approaching the 10% level for Behavioral Intention (Male =59.5%, Female = 43.2%), PEOU (Male =21.3%, Female = 10.1%), and PU (Male =47.1%, Female = 34.1%). Similarly, although there was no significant variation of path coefficients between genders at the 5% level, there was some evidence of a difference between path coefficients in terms of the impact of Compatibility on PU, but with significance only being observed at the 10% level (Male = 0.49, Female = 0.29).

Age within the sample was divided broadly into two categories; Generation X (aged between 36-56) and Generation Y (aged between 18-35). Multi-group analysis based on age as a moderator revealed a significant difference between R² values for PU, the model explaining 23.0% of variance for Generation X, and 48% of variance for Generation Y. Path coefficients varied significantly according to age in terms of the impact of Trust on Perceived Risk (Generation X= -0.34, Generation Y= -0.15). There was also some evidence of a difference between path coefficients in terms of the impact of PU on Behavioral Intention, but with significance only being observed at the 10% level, it is apparent that further work in this respect would be of use.

The final multi-group analysis focused on the method used by participants to pay for mobile phone services, being divided between those who were contract-based and those using non-contractual (pay-as-you-go) arrangements. Multi-group analysis on this basis did not reveal any significant differences between the R² values obtained. However, path coefficients varied significantly according to payment method in terms of the impact of Perceived Risk on Behavioral Intention (Contract =-0.12, Non-Contract = -0.17). There was also some evidence of a difference between path coefficients in terms of
the impact of Perceived Usefulness on Behavioral Intention, but as with the previous case, with significance only being observed at the 10% level, further work in this respect would be appropriate.

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Overall</th>
<th>Female</th>
<th>Male</th>
<th>Gen X</th>
<th>Gen Y</th>
<th>Contract</th>
<th>PAYG</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Perceived Usefulness on Behavioral Intention</td>
<td>0.30**</td>
<td>0.32**</td>
<td>0.30**</td>
<td>0.10ns</td>
<td>0.35**</td>
<td>0.37**</td>
<td>0.17ns</td>
</tr>
<tr>
<td>H2: Perceived Ease of Use on Behavioral Intention</td>
<td>0.05ns</td>
<td>0.03ns</td>
<td>0.04ns</td>
<td>0.15ns</td>
<td>0.03ns</td>
<td>0.02ns</td>
<td>0.02ns</td>
</tr>
<tr>
<td>H3: Perceived Ease of Use on Perceived Usefulness</td>
<td>0.36**</td>
<td>0.43**</td>
<td>0.31**</td>
<td>0.30*</td>
<td>0.37**</td>
<td>0.34**</td>
<td>0.46**</td>
</tr>
<tr>
<td>H4: Trust on Behavioral Intention</td>
<td>0.08ns</td>
<td>0.09ns</td>
<td>0.07ns</td>
<td>0.23ns</td>
<td>0.03ns</td>
<td>0.13*</td>
<td>0.06ns</td>
</tr>
<tr>
<td>H5: Trust on Perceived Risk</td>
<td>-0.08ns</td>
<td>-0.09ns</td>
<td>-0.21ns</td>
<td>-0.34ns</td>
<td>-0.15ns</td>
<td>-0.03ns</td>
<td>-0.04ns</td>
</tr>
<tr>
<td>H6: Perceived Risk on Behavioral Intention</td>
<td>-0.02ns</td>
<td>-0.18ns</td>
<td>-0.06ns</td>
<td>-0.11ns</td>
<td>-0.1ns</td>
<td>-0.12ns</td>
<td>-0.17ns</td>
</tr>
<tr>
<td>H7: Compatibility on Perceived Usefulness</td>
<td>0.42**</td>
<td>0.29*</td>
<td>0.49**</td>
<td>0.26ns</td>
<td>0.46**</td>
<td>0.46**</td>
<td>0.36**</td>
</tr>
<tr>
<td>H8: Compatibility on Perceived Ease of Use</td>
<td>0.41**</td>
<td>0.30**</td>
<td>0.46**</td>
<td>0.43ns</td>
<td>0.38**</td>
<td>0.37**</td>
<td>0.48**</td>
</tr>
<tr>
<td>H9: Compatibility on Trust</td>
<td>0.38**</td>
<td>0.32**</td>
<td>0.46**</td>
<td>0.46**</td>
<td>0.34**</td>
<td>0.42**</td>
<td>0.33**</td>
</tr>
<tr>
<td>H10: Compatibility on Perceived Risk</td>
<td>0.48**</td>
<td>0.47ns</td>
<td>0.54**</td>
<td>0.37ns</td>
<td>0.51**</td>
<td>0.45**</td>
<td>0.61**</td>
</tr>
<tr>
<td>H11: Compatibility on Behavioral Intention</td>
<td>0.49**</td>
<td>0.48*</td>
<td>0.51**</td>
<td>0.45*</td>
<td>0.49**</td>
<td>0.42**</td>
<td>0.54**</td>
</tr>
</tbody>
</table>

**Table 3. Summary of Results**
(*significant at 5% level)

**Discussion**

Against a backdrop of practical relevance and need for further empirical work, particularly in non-traditional areas predicted to experience substantial mobile data traffic growth, this study contributes to the body of knowledge of consumer adoption of m-payments. Using a technology acceptance perspective as a theoretical basis, and employing insights from the extant related literature, an extended version of TAM was tested using primary data, explaining 53.3% of the variance in intention to use m-payments; with a Q² value of 0.42 for intention to use, the predictive relevance of the model is evident.

Two of the core relationships of TAM received empirical support, with PU having significant positive effects on consumers’ intentions to use m-payments, and PEOU having a positive and significant influence on PU. However, the positive relationship between PEOU and consumers’ intentions to use m-payments did not receive particular support in this study. In other words, whether or not m-payments were perceived as being easy to use influenced the user’s intention to use only indirectly via the perception of usefulness.

Moreover, trust was found not to significantly influence consumers’ intentions, hypothesis H4 being marginally rejected (apart from in the case of contract payment consumers, in which there was support at the 5% level). This outcome is generally aligned with the results of Luo et al. (2010) in their study of m-banking, but contrasts with results of studies on mobile technologies such as those by Chandra et al. (2010) and Chong et al. (2012). Further work is therefore appropriate, given the conflicting views across studies. There was also lack of evidence in this study to support the expected negative relationship between trust and perceived risk (H5), which again is aligned with the results of Luo et al. (2010) in their study of m-banking. This aspect requires further investigation.

Risk performed well as a formative construct, all six contributing components being significant at the 1% level, with time, psychological, and social risk presenting the strongest relationships with perceived risk. This contrasts somewhat with the results of Luo et al. (2010) in which risk was
similarly modeled as a formative higher-order component, but in which financial, performance, and
dependency risks formed the strongest relationships, and social risk was not significant. Given that the
survey of Luo et al. (2010) was conducted in the USA, it is feasible that cultural differences are
influential in the varying of consumers' perceptions of the facets of risk, and further work relating to
this aspect would be beneficial.

The hypothesis (H6) that risk has a negative impact on consumers' intention to adopt m-payments
received some support, a weak relationship being significant at the 10% level. Given that this study is
among the first to model risk as formative higher-order component in the context of m-payment
acceptance, additional work would be appropriate to further investigate the relationship between
perceived risk and consumers' intention to adopt m-payments.

Empirical support was found for compatibility having a significant positive influence on PU (H7), on
PEOU (H8), on trust (H9), and on consumers' intentions to use m-payment services (H11). These
results are in line with those in the studies of Aldás-Manzano et al. (2009) and Schierz et al. (2010),
among others, all of which also examined mobile technologies. However, surprisingly, there was no
support for compatibility having the expected negative influence on users' perceived risk relating to
m-payment use (H10), the relationship between compatibility and risk being found to be positive and
significant. Given the multi-dimensional treatment of risk in this study, and the particular cultural
setting, clearly this is an aspect demanding further attention.

Calculation of total effects produced a ranking among factors in terms of performance as drivers of m-
payment adoption. Additional insights were provided by an impact-performance analysis (Volckner et
al. 2010) conducted at construct level, the combination of these techniques highlighting areas suitable
for managerial attention by providing greater understanding of how the various constructs impact on
the dependent variable. Results of this activity suggest that perceived compatibility has the largest
impact on intention to use m-payments, hence reinforcing the key challenge to providers of m-
payment services as being to market these facilities in a way that convinces consumers of their
compatibility with their values and needs. The second most influential factor in this study was
perceived usefulness - m-payment providers could therefore potentially increase adoption levels by
emphasizing this aspect of the service. The implication is that within the cultural context examined,
intention to use m-payments is primarily driven by compatibility and perceived usefulness. Further
work on the promotion of these aspects would therefore be of use.

By modeling risk as a multi-dimensional formative construct, this study highlights those aspects of
risk most likely be of concern to consumers, and hence more likely to delay the adoption of m-
payments. This information can be used by providers of m-payment services to manage concerns
regarding those elements viewed as causing most anxiety. Although all six risk facets were found to be
significant, those perceived as causing most concerns were time, psychological, and social risk.
Appropriate countermeasures could therefore be emphasized when marketing m-payment services in
order to increase the likelihood of consumers making the adoption decision. For instance, providers
may accentuate the convenience, accessibility, and reliability of m-payments, hence reducing the
potential for time loss concerns. Marketing activities may also highlight the desirability and
contemporary nature of the services, in order to reduce possible psychological and social risk
perceptions. Concerns over possible financial risk may be mitigated by highlighting the anti-fraud
security features of the technical infrastructure, and by the provision of financial protection
procedures and policies.

There are limitations to this study in that the sample size was restricted, and the data obtained from a
single cultural and contextual setting. It would be useful to extend the study to include non-
professionals, a broader age range, and also investigate perceptions of existing users of m-payments.
Results obtained also suggest it would be useful to test the model in additional cultural settings, and to
investigate possible issues of metric invariance across groups/cultures.

This study presents a number of practical implications for those responsible for marketing and/or
managing m-payment services. The findings are particularly pertinent, given that the perceived
potential of m-payments is not reflected in current adoption rates, with consequent revision of
anticipated growth figures. The motivation for this study was to investigate factors influencing the
adoption decision by consumers, and while the exploratory nature of the work does not facilitate
large-scale policy development, a number of managerial implications may be drawn.
Conclusion

This paper proposed a model of consumer acceptance of m-payments by extending core TAM components with constructs which have attracted attention from marketing researchers investigating consumer perceptions of innovations; perceived risk, trust, and compatibility. The model was tested with primary data gathered from a survey of potential m-payment users in a developing country in the Middle East/Africa block — part of region predicted to experience substantial mobile data traffic growth over the next few years. The model received good empirical support, explaining 53.3% of variance in consumer intention to make use of m-payments. The paper contributes to m-payment services research by highlighting key influencing factors (particularly the importance of compatibility) and the forms of risk presenting most concern, and by identifying aspects appropriate for managerial attention. The study identifies numerous areas requiring further investigation, and hence can serve as a foundation for additional research into consumer acceptance of m-payments.

To our knowledge, this is the first study which has both modeled risk as multidimensional construct, and performed a multi-group analysis making use of three moderating variables in an attempt to understand how overall variance and path coefficients within the extended model alter according to moderator categories. However, we acknowledge a number of limitations. While the sample size is sufficient for PLS analysis, sample sizes subsequently available for the multi-group analysis (which required the sample to be divided into two categories in each case) were naturally smaller. Further study would therefore attempt to collect a larger amount of data. Additional work would also engage adopters, and incorporate ‘actual use’ into the model.

REFERENCES


