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FIRM TECHNOLOGY ADOPTION MODEL (F-TAM) AMONG SME'S: AN INTERACTIVE ECO-SYSTEM PERSPECTIVE

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ABSTRACT

This paper seeks to test the Firm Technology Adoption Model (F-TAM) using data from a developing country context. The data for this current study were purposively collected from four hundred (400) SMEs in the Greater Accra Region of Ghana. We used partial least squares structural equation modeling (PLS-SEM) for our data analysis. Data revealed that, whereas employee factors can lead to firm adoption, firm factors of adoption do not lead to firm adoption if societal factors, characteristics of the innovation, and employee factors do not moderate the relationship between firm factors and firm adoption. Data also reveals that societal factors do not lead to firm adoption if employee factors do not mediate it. The theoretical contribution of this study is that it challenges the dominant idea in most of the earlier models that firm adoption of innovation will be realized, without reference to factors at other levels of adoption. This positioning of the F-TAM model is a significant departure from earlier models. For industry practitioners, these findings illustrate the essence of putting a premium on recruiting technologically savvy employees if the firm intends to adopt digital technologies.

KEYWORDS

Firm Technology Adoption Model (F-TAM), SMEs, Developing Countries

1. INTRODUCTION

Studies on the adoption of various technologies continue to engage the attention of researchers in different spheres of study (Oliveira & Martins, 2011; Shanker, Vankatesh, Hofacker, & Naik, 2010; van Frederici, Ravesteijn, & de Waal, 2016; Mavi & Standing, 2017; Overby & Ransbotham, 2019; Wunderlich, Veit, & Sarker, 2019). Such studies have generally engaged personal level, firm level, and societal level adoption models (Rogers, 2010). The few models that focus on organizational/firm level adoption include the Technology Organization and

Environment (TOE) framework (Yeboah-Boateng & Essandoh, 2014) to understand contextual issues relevant for firm adoption; Task-Technology Fit (TTF) (Goodhue & Thompson, 1995) to understand individual behaviour with technology in a firm setting; and Perceived Electronic Readiness Model (PERM) (Molla & Licker, 2005) to understand the preparedness of firms in technology adoption. The Diffusion of Innovations Theory (Rogers, 1962) considered the oldest of all the adoption models, also explains adoption at all three levels of adoption. Various scholars have examined these earlier models within different contexts such as developing countries and on different technologies. Examples of such studies include the use of TAM and DOI to examine the adoption of mobile money in Ghana at the individual level (Tobin & Kuwornu, 2011), TAM on banking in Ghana (Crabbe, Standing, Standing, & Karjaluoto, 2009) among other studies. A dominant idea in the many research streams that studied adoption of innovations at the individual, firm or societal level of adoption is the impression created in the models that the antecedents of behavioral intention to adopt an innovation are enough to lead to adoption; an idea that has been questioned when contextual issues are taken into consideration (Data, 2011). A major implication is that further studies on technology adoption in developing countries need to use or develop models and instruments with the contexts as a significant consideration. This argument for context relevant models and instruments is based on the premise that the need to ground research in context is as strong as the need to ground research in the international scientific discourse (Röling, Hounkonnou, Offei, Tossou, & Van Huis, 2004). It is also premised on the idea that adopters' choices regarding adoption are based on rationality embedded in culture and the context of adoption rather than persuasion (Agarwal, 1983; Dewan & Kraemer, 2000; Shih, Venkatesh, Chen, & Kruse, 2013; Amoako, Doe, & Deheer, 2014).

In Ghana, this quest for context relevant factors that lead to the adoption of innovation has increased owing to the current discussion of factors that explain the swift adoption of mobile technologies, particularly mobile money financial technology popularly referred to as mobile money (Attopley, 2016; Tagoe, 2016; Bank of Ghana, 2016). The revised Firm Technology Adoption Model (F-TAM) (Doe et al., 2018) sought to explain the adoption of mobile innovations at the SME level. The F-TAM model views the personal level factors, firm/industry factors, and societal level factors that interact in an ecosystem of adoption. The model attempts to examine the effect and role of personal level factors as well as societal level factors in the environment of firm technology adoption. This contribution to scholarly discussion on context relevant models was a significant departure from the earlier norm of adapting constructs into a current study (Data, 2011; Brown, Venkatesh, Kuruzovich, & Massey, 2008). This novel track of measuring firm level adoption of an innovation, while accounting for the influence of other levels of adoption (personal level and societal level), and with the model developed from the socio-cultural context of adoption, set forth a new stream of adoption studies. Paramount among such new streams of studies include the development of measuring instruments, quantitatively testing the instrument in similar contexts, validation of the model with data across countries, and comparative study of the F-TAM model and other models. This study, therefore, aims to *quantitatively test the proposition in one of the current context relevant models, the revised firm technology adoption model (F-TAM), using data collected from Ghanaian SMEs* who adopted mobile money as part of their business operations. Mobile money is used to test this model due to its rapid diffusion ahead of other technological innovations and thus presents an event to test the F-TAM on.

2. THEORETICAL BACKGROUND

This section highlights categories of the earlier models, examines the firm level models and their inherent weakness in addressing the contextual gap being addressed in this study, and finally presents the F-TAM model and its propositions in the form of hypotheses to be tested in this study.

2.1 Previous Literature on Adoption of Innovations

Theories or models used in studying innovations at the personal level of adoption include the Diffusion of Innovations Theory (DOI) (Rogers, 1962), Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behaviour (TPB) (Ajzen, 1985), Decomposed Theory of Planned Behavior (DTPB) (Taylor & Todd, 1995), Integrated Model of Technology Acceptance (IMTA) (Venkatesh, Speier & Morris, 2002), TAM (Venkatesh & Bala, 2008), The Unified Theory of Acceptance and Use of Technology (UTAUT 1 & 2) (Venkatesh, Thong & Xu, 2012), and Dynamic Use Diffusion Model (DUDM) (Shih, Venkatesh, Chen, & Kruse, 2013). Models developed for the study of societal level adoption include Culture, Policy & Technology Framework (CPT) (Bajaj & Leonard, 2004). At the firm level, models such as Technology, Organization and Environment Framework (TOE) (Tornatzky, Fleischer & Chakrabarti, 1990), Task-Technology Fit (TTF) (Goodhue & Thompson, 1995), and Perceived Electronic Readiness Model (PERM) (Molla & Licker, 2005) have been developed to examine adoption of innovations.

The Task-Technology Fit (TTF) (Goodhue & Thompson, 1995) attempts to explain the link between individual performance and information systems (innovations) in an organizational context. It proposed that, for technology innovation to have an impact on individual performance, the technology must be utilized, and have a fit between the task to be performed and the characteristics of the technology to be used in performing the task.

The Perceived Electronic Readiness Model (PERM) (Molla & Licker, 2005) proposed a model of examining firm adoption of digital technologies in developing country contexts. The model is based on perceived organizational e-readiness (POER) and perceived environmental e-readiness (PEER). The model posits that awareness of innovation, human resources, business resources, commitment, and governance are POER factors that can make an organization ready for adoption. The model also posits government eReadiness, market forces eReadiness and supporting industries eReadiness as PEER factors that support firm adoption of technology adoption. The PERM model suggests that these PEOR and PEER factors influence initial adoption and institutionalization of the digital technology. The model, however, does not attempt to examine the relationship between the factors.

The Diffusion of Innovations Theory (DOI) (Rogers, 1962) is a theory of how, why, and at what rate new ideas and technology spread through cultures, operating at the individual and firm level. At the firm level, the DOI theory proposes that innovativeness is related to leader characteristics, internal organizational structural characteristics, and external characteristics of the organization. Leader characteristics describe the leaders’ attitude toward change. Internal characteristics and organizational structure includes the extent of *centralization* (the degree to which power and control in a system are concentrated in the hands of a few individuals), *complexity* (the degree to which an organization’s members possess a relatively high level of knowledge and expertise), and *formalization* (the degree to which an organization emphasizes its members following rules and procedures). It also includes *interconnectedness* (the degree to which the units in a social system are linked by interpersonal networks), *organizational slack* (the degree to which uncommitted resources are available to an organization), and *size* (the number of employees of the organization). External characteristics of an organization refers to a system or organizational openness to external influences. This model links the factors directly to adoption, but does not examine how they interrelate.

The TOE framework (Tornatzky & Fleischer, 1990) identifies three particular domains of an enterprise's context that influence the process by which it adopts and implements a technological innovation. These are technological context, organizational context, and environmental context. The technological context describes both the internal and external technologies available to the firm. Organizational context is a descriptive measure of the organization, such as scope, size, and managerial structure. The environmental (business ecosystem) context is the arena in which a firm conducts its business, such as its industry, competitors, and dealings with the government. The model does not examine the interrelationships of the factors.

On closer scrutiny of the different models, the TOE framework provides a useful analytical tool that scholars can use to study the adoption and respective assimilation of different types of digital innovation in a firm setting. The TOE framework is consistent with the DOI theory, in which Rogers (1995) emphasized individual characteristics, and both the internal and external characteristics of the organization, as drivers for organizational innovativeness. TOE framework, however, includes the environmental context, which is absent from DOI. DOI furthermore emphasizes the characteristics of the leader, which is absent from the TOE. The PERM model is consistent with the TOE and DOI to the extent that it highlights organizational factors and environmental factors that influence adoption. None of the models highlight the role of employees as individuals in the firm. It appears that Rogers' (1962) innovation diffusion theory is better able to explain intra-firm innovation diffusion while the other models explain general firm adoption (Hsu et al., 2006). A common issue that runs through these models, however, is that they do not examine the interrelationship between the various factors. The TTF for instance only suggests that technology characteristics is a relevant factor for the innovation even to be considered for adoption, but does not consider the influence of human perceptions on the technology, and vice versa. The application of these models in developing countries has been reported to yield varying results (Datta, 2011), highlighting the need for models that are developed with data from a developing county context.

Recent scholarly discussion of digital technologies such as data mining, cloud computing, social media, cybersecurity, and mobile applications, have witnessed a strong emphasis on adoption studies (Masocha & Dzomonda, 2018; Asongu, 2018; Adjei & Odei-Appiah, 2018). Such studies in Ghana include Adadevoh (2018), Adjei and Odei-Appiah (2018) and Ansong and Boateng (2018). Similar studies in other developing countries include Chaouali, Souiden, and Ladhari (2017), Asongu (2018) and Masocha and Dzomonda (2018). A fundamental issue worth noting among these studies is that none of them was done with a model initially developed from a developing country context. Perhaps, the F-TAM model will serve as a trail-blazer in this long-awaited track to context-specific models. Following the groundbreaking study of Doe et al. (2018) on the F-TAM, a F-TAM measuring instrument (Doe et al., nd) was subsequently developed to aid researchers to measure or study firm technology adoption among SMEs.

2.2 F-TAM

The revised F-TAM (Doe et al., 2018) was a contextual verification of the initial F-TAM (Doe et al., 2017) through two rounds of Delphi panel interviews of both academics and industry experts. To understand the model refinement process, a highlight of the Delphi process in that study is worth mentioning here. In the first round of interviews, ten industry expert were purposively sampled (Saunders et al., 2007; Yin 1994) from an industry awards list, showing the firms that introduced the most adopted mobile digital innovations. The participants were completely anonymous. Five academic participants were sampled using a snowballing technique of academics who had published in the area of study. Academic membership of respondents was therefore not entirely anonymous. The respondents commented on the original variables and relationships of the F-TAM (Doe et al., 2017). New variables and relationships that were not part of the initial model were discovered and added to the model for the second round of interviews. In the second round, respondents commented on the revised variables, restricting the comment to an agreement, disagreement, and neutrality. The researcher's role in the process was restricted to that of a planner, facilitator, recorder and reviewer or synthesizer of the data (Avella, 2016).

Delphi interviews were administered orally and recorded, or sent by email. Voice data was transcribed into text, using content analysis and pattern matching (Yin, 2013; Ezzy, 2002) to scan out the main issues being discussed and to confirm, add to or subtract from the original model. Cross-case analysis was conducted using the concept-centric approach (Webster & Watson, 2002) to assemble the discussion into building blocks or themes that refine the existing model with pattern matching (Yin, 2013). A variable index was developed in that study and used to determine the weight of consensus for each variable or relationship agreed upon by the end of the second round (Doe et al., 2018). These validation processes captured new constructs and propositions that refined the original F-TAM. A critical construct introduced in the revised model, for instance, is the construct of technology characteristics, which was not anticipated in the initial model. This oversight was due to the initial F-TAM focus on the inter-relationship between the three levels of adoption. The relevance of the original F-TAM is that it theorizes an interrelationship between the three levels of adoption and its effect of firm adoption. The relevance of the revised F-TAM is also that it accounts for other contextual variables and constructs not anticipated in the original model, and confirms technology factors (Rogers, 1962) as a relevant consideration in the ecosystem of the firm technology innovation adoption.

The revised F-TAM proposes that employee level variables (personal level factors) of *Perceived Ease of Use, Perceived Usefulness, Perceived Indispensability, Perceived Social Influences*, *Trial Feedback*, and *Employee Self Enhancement Motives* will collectively lead to firm adoption, and influence firm factors of adoption. Following the model's logic, Doe et al. (2018) proposed the following hypotheses:

H1: Personal level factors lead to firm adoption

H2: Personal level factors influence firm factors

At the firm level, the revised F-TAM (Doe et al.,2018) decomposes the general firm-level factors into internal organizational factors such as *Technological Readiness Managerial Innovativeness, Organizational Readiness, Strategic Fit with Operations, Ease of Support, and Organizational Culture;* and firm industry factors such as *Customer Needs/Demand, Competitive Pressure,* and *Partner Requirement*. The model posits that these factors will be combined at the firm level to influence firm adoption. An unnamed proposition in this model is that those firm internal characteristics, as well as industry factors, will, separately, lead to firm readiness to adopt, and firm adoption. These propositions are not tested in this study but are worth testing within the same framework of examining the relationship between firm factors, other levels of adoption, and technology characteristics. The revised F-TAM model, therefore, hypothesizes that

H3: Firm factors lead to firm adoption

Societal level factors proposed in the revised F-TAM (Doe et al., 2018) are *Government Policy, Government Championship, Government Laws, Innovation Infrastructure, Opinion Leadership,* and *Successive Government Commitment.* The model posits that these will, taken together, lead to firm adoption, influence employee factors, influence firm factors, and moderate the relationship between firm factors and firm adoption. The relationship between societal level factors and firm adoption was initially not anticipated in the study of Doe et al. (2017) but has become relevant. These particular relationships are hypothesized as follows:

H4: Societal level factors influence personal level factors

H5: Societal level factors influence firm-level factors

H6: Societal level factors lead to firm adoption

Rogers (1962) theorized how the characteristics of innovation affect its adoption. Apart from the CTP model, later theories and models that focused on technology adoption did not anticipate this construct of technology characteristics. This oversight is largely because the models focused on human behavioral intention to adopt at the various levels of adoption. The revised F-TAM, however, has placed great emphasis on the technology characteristics as a strong influence on individuals, firms, and society at large. These technology characteristics are *Observability, Flexibility, Complexity,* and *Relative Advantage* (Rogers, 1962). Doe et al. (2018) propose that the characteristics of the innovation/technology will influence employee level factors, influence firm-level factors, and influence societal level factors.

They are hypothesized in this study as follows:

H7: Technology factors influence employee factors

H8: Technology factors influence firm-level factors

H9: Technology factors influence societal factors

3. METHODOLOGY

The data collection instrument was designed and validated by an evaluation process of self review, expert review of four experts, and focus group discussion involving twelve academics (Leeux et al., 2008). Question items in the instrument were either adapted from relevant previous studies related to the purpose of this study or crafted and taken through the evaluation process. During the evaluation process, the authors checked for length of the question (Holbrook et al., 2006; Fink, 2003); grammar (Donyei, 2003; Leeux et al., 2008); simplicity (Bhandari & Wagner, 2006); social desirability (Brace, 2004); double-barreled questions (Leeux et al., 2008); and question order (Baker, 2003). The instrument was furthermore taken through a field test (Leeux et al., 2008) with a sample size of 25 respondents (Fowler, 1995; Converse & Presser, 1986; Sheatsley, 1983; Sudman, 1983; Converse & Presser, 1986). The instrument was found to be valid and reliable (see Doe et al., nd) in testing SME for the F-TAM of technology adoption at the firm level.

We purposively sampled (Straits & Singleton, 2017) data for the current study from 400 SMEs from the Greater Accra Region of Ghana. The Greater Accra Region of Ghana represents the most cosmopolitan and diverse SME population. The 400 responses obtained from the SME survey met the PLS analysis recommendation proposed by Barclay et al. (1995). They propose 10 times the number of structural paths directed at a particular construct in the inner model (in this case firm adoption had the highest number of predictors - 25; therefore, the minimum sample is 250). Thus, the obtained sample size of 400 for this study meets the minimum sample size requirement for the application of PLS-SEM.

Trained data collectors were engaged to collect data. Steiger (1988) emphasizes that the specific statistical tools used in the quantitative analysis must be reported to support a reliable replication of a study. This study used Partial least squares structural equation modeling (PLS-SEM) (SmartPLS Release: 3.2.7) (Ringle et al., 2015) for the data analysis. Except for firm adoption, constructs were measured reflectively because the individual items were similar and correlated well, such that the deletion of some items did not significantly affect the definition of the construct. Model indicators are suggested by the underlying construct and have positive and desirably high intercorrelations (Coltman, Devinney, Midgley, & Veniak, 2008).

4. DATA ANALYSIS

4.1 Descriptive Statistics of Data

We included details concerning the demographics of the respondents in Appendix. For the data used in testing the model, twenty-six (26) main constructs were examined in this study and are shown in Table 1. A mean score of approximately 4 (Agreed) was obtained for firm adoption, all the six variables of personal factors, except perceived indispensability; all the six variables of firm internal factors, except ease of support; all the three variables of firm external factors, all the six variables of societal factors, and all the four variables of technological characteristics. Furthermore, all the measurement constructs are statistically significant at $p<0.01$ (or $p<0.05$). That is, t-values are all greater than 1.96 using a 0.05 level of significance (Hair et al., 2016). This finding implies that all the attributes identified in this study regarding firm level adoption of mobile money implementation and its antecedents are applicable to SMEs in Ghana.

Table 1. Descriptive Statistics for All Constructs (N=400)

Constructs	**Mean**	**S.D**	**t**	**p**
Firm Level Adoption of MoMo Innovations	4.082	0.497	43.498	0.00***
Perceived Ease of Use	4.001	0.547	36.597	0.00***
Perceived Usefulness	3.875	0.616	28.388	0.00***
Perceived Indispensability	3.315	0.833	7.564	0.00***
Perceived Social Influences	3.636	0.768	16.552	0.00***
Trial Feedback	3.785	0.620	25.332	0.00***
Employee Self Interest/Self Enhancement Motives	3.571	0.770	14.825	0.00***
Technological Readiness	3.733	0.728	20.116	0.00***

Managerial Innovativeness	3.813	0.663	24.515	0.00***
Organisational Readiness	3.821	0.630	26.055	0.00***
Strategic Fit with Operations	3.778	0.693	22.464	0.00***
Ease of Support	3.477	0.837	11.401	0.00***
Organisational Culture (Firm propensity to take risk)	3.749	0.711	21.073	0.00***
Organisational Partner Requirement	3.751	0.683	22.004	0.00***
Competitive Pressure	3.698	0.687	20.321	0.00***
Needs of Customers	3.705	0.659	21.396	0.00***
Government Championship	3.698	0.701	19.890	0.00***
Government Policy	3.558	0.665	16.756	0.00***
Government Regulation/ Laws	3.668	0.697	19.144	0.00***
Innovation Infrastructure	3.911	0.689	26.456	0.00***
Opinion Leadership	3.711	0.662	21.478	0.00***
Successive Government Commitment	3.695	0.649	21.427	0.00***
Flexibility	3.924	0.619	29.877	0.00***
Observability	3.828	0.651	25.430	0.00***
Complexity	3.600	0.679	17.683	0.00***
Relative Advantage	3.843	0.672	25.090	0.00***

Note: ***significant at $p<0.01$. Source: Field Data (2018)

4.2 Data Suitability/Quality Test

To performing structural equation modeling, it is essential to satisfy data quality criteria of non-response bias, common method variance bias, sample size adequacy, and normality test to ensure the appropriateness of the data for analysis.

Non-response Bias- This survey was completed under conditions of anonymity with a response rate as high as 95%, creating the basis for avoidance of non-response bias (Ledden et al., 2011). The authors, however, compared the mean values of the questionnaire scale items between early respondents and late respondents and found no significant difference between the two categories (Lings & Greenly, 2010). Therefore, non-response bias was not likely to be a problem with this data.

Common Method Variance Bias- Harman (1967) recommends exploratory factor analysis (EFA) with the extraction of only one factor. If the factor extracted has less than 50% variance, then common method variance bias is not likely to be a problem. Andersson and Bateman (1997), Podsakoff et al. (2003) and Lings and Greenly (2010) likewise approved of this technique. EFA conducted on the survey data with the extraction of only one factor shows that the factor accounts for 23.9% variance (which is less than 50% variance). Hence, common method variance bias is absent from this data. See Appendix.

Sample Size Adequacy- Data sample adequacy and the criteria used is described under methodology (See section 3)

Normality diagnostics- Normality tests were conducted by examining skewness, kurtosis, Kolmogorov-Smirnov tests, and Shapiro-Wilk test. An analysis of the scales used in the study questionnaire indicated that thirty-two (32) items had kurtosis > ±1.0; whereas seventeen (17) items had skewness > ±1.0. More importantly, the Kolmogorov-Smirnov test of normality showed that $0.222<\alpha<0.329$; $p<0.01$ for all items. Similarly, the Shapiro-Wilk test of normality showed that $0.776<W< 0.895$; $p<0.01$ for all items. These results imply that the data violates multivariate normality assumptions, thus confirming the appropriateness of the usage of PLS-SEM.

4.3 Assessment of The Measurement Model

Confirmatory factor analysis tests of convergence and discriminant validity for the reflective constructs (Lings & Greenly, 2010; Hair et al., 2016) are significant for structural equation models. Minimum Cronbach's alpha recommended for adequate convergent validity is 0.6 for exploratory studies (Hair et al., 2016; Chin, 2010). Minimum composite reliability and average variance extracted (AVE) estimates recommended are 0.7 and 0.5 respectively (Hair et al., 2016). Guided by these recommendations, results for the convergent validity test for the measurement model in Table 2. An examination of the initial loadings showed that ***Personal Factors*** was measured using six constructs, with three items under various constructs loading below the minimum threshold. ***Firm Internal Factors*** was measured using six constructs with two items under different constructs loading below the minimum threshold. ***Firm External Factors*** was measured using three constructs, with two items under *organization partner requirement*, two items under *needs of customers*, and one item under *competitive pressure* all of which had loadings below the minimum threshold. ***Societal Factors*** was measured with six constructs, with two items under *government championship*, and four other items under various constructs all loading below the minimum threshold (Hair et al., 2016). ***Technological Characteristics*** was measured using four constructs, with four items under various constructs loading below the minimum threshold. All items with loadings below the minimum threshold (all had loadings below the minimum threshold of 0.6 (Hair et al., 2016) were deleted, and the model re-run to obtain acceptable loadings. Therefore, following recommendations by Hair et al. (2016) and Chin (2010) convergence validity has been met for the six constructs under personal factors, six constructs under firm internal factors, three constructs under firm external factors, six constructs under societal factors, and four constructs under technological characteristics.

Table 2. Convergence & Discriminant Validity of Reflective Constructs (Square root of AVEs in diagonal bold)-Fornel & Lacker Criterion

Constructs	CA	CR	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1. Firm Level Adoption	**NA**	**NA**	**NA**	**NA**																									
2. Perceived Ease of Use	0.61	0.79	0.56	0.37	**0.75**																								
3. Perceived Usefulness	0.62	0.80	0.57	0.41	0.37	**0.76**																							
4. Perceived Indispensability	0.74	0.84	0.56	0.29	0.22	0.33	**0.75**																						
5.Perceived Social Influences	0.69	0.81	0.60	0.17	0.15	0.24	0.50	**0.77**																					

6. Trial Feedback	0.66	0.81	0.59	0.22	0.25	0.24	0.36	0.42	**0.77**																				
7. Employee Self Interest	0.74	0.84	0.56	0.36	0.18	0.41	0.51	0.47	0.45	**0.75**																			
8. Technological Readiness	0.73	0.83	0.54	0.25	0.15	0.24	0.46	0.46	0.44	0.52	**0.74**																		
9. Managerial Innovativeness	0.62	0.78	0.54	0.17	0.17	0.16	0.36	0.42	0.44	0.46	0.48	**0.74**																	
10. Org. Readiness	0.67	0.81	0.59	0.28	0.18	0.23	0.43	0.44	0.52	0.51	0.58	0.44	**0.77**																
11. Strategic Fit with Ops.	0.74	0.84	0.56	0.25	0.20	0.23	0.41	0.51	0.56	0.54	0.50	0.50	0.57	**0.75**															
12. Ease of Support	0.80	0.87	0.62	0.30	0.22	0.35	0.49	0.41	0.30	0.54	0.45	0.32	0.41	0.43	**0.79**														
13. Organisational Culture	0.71	0.81	0.52	0.30	0.24	0.30	0.37	0.36	0.31	0.43	0.43	0.46	0.39	0.44	0.46	**0.72**													
14. Org. Partner Requirement	0.67	0.81	0.59	0.19	0.09	0.24	0.47	0.49	0.35	0.47	0.49	0.38	0.47	0.43	0.59	0.49	**0.77**												
15. Competitive Pressure	0.65	0.81	0.58	0.18	0.15	0.27	0.41	0.45	0.43	0.52	0.43	0.43	0.47	0.51	0.42	0.47	0.48	**0.76**											
16. Needs of Customers	0.62	0.80	0.57	0.23	0.19	0.26	0.44	0.41	0.34	0.39	0.39	0.39	0.38	0.40	0.43	0.51	0.54	0.55	**0.75**										
17. Govt. Championship	0.77	0.83	0.56	0.13	0.21	0.18	0.46	0.46	0.41	0.40	0.35	0.43	0.35	0.43	0.41	0.46	0.51	0.47	0.47	**0.75**									
18. Government Policy	0.63	0.80	0.57	0.26	0.20	0.23	0.37	0.43	0.28	0.32	0.39	0.34	0.30	0.29	0.41	0.36	0.35	0.37	0.43	0.41	**0.75**								
19. Govt. Regulation/ Laws	0.61	0.79	0.55	0.34	0.23	0.28	0.35	0.39	0.40	0.43	0.29	0.34	0.40	0.44	0.34	0.39	0.28	0.40	0.43	0.33	0.55	**0.74**							
20. Innovation Infrastructure	0.68	0.83	0.61	0.15	0.19	0.11	0.19	0.26	0.26	0.20	0.29	0.27	0.28	0.25	0.19	0.27	0.26	0.32	0.38	0.32	0.45	0.52	**0.78**						
21. Opinion Leadership	0.69	0.80	0.51	0.17	0.08	0.24	0.34	0.44	0.24	0.37	0.38	0.31	0.39	0.41	0.46	0.39	0.52	0.46	0.50	0.46	0.55	0.46	0.47	**0.71**					
22. Successive Govt Commit.	0.76	0.86	0.66	0.21	0.19	0.15	0.33	0.47	0.42	0.37	0.36	0.46	0.38	0.49	0.30	0.42	0.39	0.53	0.46	0.54	0.50	0.51	0.53	0.58	**0.81**				
23. Flexibility	0.65	0.81	0.59	0.18	0.21	0.20	0.21	0.32	0.32	0.20	0.19	0.18	0.25	0.29	0.22	0.29	0.23	0.36	0.39	0.45	0.42	0.38	0.51	0.45	0.53	**0.76**			
24. Observability	0.72	0.83	0.63	0.18	0.16	0.17	0.26	0.41	0.43	0.26	0.26	0.31	0.37	0.48	0.36	0.37	0.41	0.47	0.45	0.47	0.43	0.45	0.46	0.50	0.58	0.60	**0.79**		
25. Complexity	0.70	0.83	0.62	-0.12	-0.21	-0.23	-0.34	-0.45	-0.36	-0.38	-0.36	-0.32	-0.35	-0.45	-0.41	-0.39	-0.48	-0.48	-0.39	-0.38	-0.33	-0.37	-0.34	-0.47	-0.46	-0.31	-0.44	**0.79**	
26. Relative Advantage	0.67	0.82	0.60	0.33	0.28	0.28	0.33	0.40	0.42	0.46	0.33	0.38	0.41	0.43	0.42	0.42	0.44	0.51	0.48	0.50	0.46	0.50	0.47	0.44	0.58	0.49	0.57	-0.48	**0.77**

All correllations are positive and mostly significant (Source: Field Data 2018)

4.4 Discriminant Validity Assessments

Discriminant validity is about the uniqueness of a construct. Hair et al. (2016) and Hensler et al. (2015) recommend assessing the Fornell-Lacker criterion, item cross-loadings, and the heterotrait-monotrait ratio (HTMT) criterion to test discriminant validity. Henseler et al. (2015) argued that cross-loadings of indicators explain zero percent of discriminant validity while Fornell-Larcker and HTMT criterions explained 20.82 percent and 97 to 99 percent of discriminant validity respectively. This study, therefore, examines the discriminant validity of the reflective constructs using Fornell-Larcker and HTMT criteria.

Discriminant Validity- Fornell-Larcker Criterion- The square root of the average variance extracted estimates for each of the 25 reflective constructs is higher than the inter-construct correlations between them (Fornell & Lacker, 1981; Hair et al., 2016). Thus, each construct is distinct and differs from the other measurement constructs in the model hence discriminant validity is met, as shown in Table 1 and 2.

Discriminant Validity- Heterotrait-Monotrait Ratio- Although Henseler et al. (2015) provided three HTMT criteria: HTMT specificity ratio of 0.90, HTMT specificity ratio of 0.85 and HTMT inference score ranging from -1 to 1 ($-1 < HTMT < 1$) as an indication of distinctiveness, they argued that HTMT.85 is the most conservative criterion. HTMT inference is the most liberal while HTMT0.9 lies in between the two extreme categories in terms of specificity rates. The authors, therefore, adopt the 0.9 ($HTMT_{0.9}$) as a criterion for assessing discriminant validity (Gold et al., 2001; Teo et al., 2008; Henseler et al., 2015). The HTMT result presented in this study shows that none of the correlations exceeded 0.9, thus confirming discriminant validity for the 25 reflective constructs in the model.

4.5 Testing for Multicollinearity of Formative Scale Measure- Firm Adoption of Mobile Money Innovations

Firm adoption of mobile money innovations was modeled in a formative mode. Several authors, including Hair et al. (2014), recommend testing for multicollinearity of the formative indicators (items) to ensure a valid data quality test. A multicollinearity test was conducted for the five items under the firm adoption of mobile money innovations construct. An examination of the variance inflation factors (VIF) showed that multicollinearity does not exist since all items had VIF<5, as shown in Table 3.

Table 3. Assessmetn of multicollinearity for Firm Adoption of Mobile Momey (Momo) Innovations (showing VIF values)

Firm Adoption items	**VIF**
My firm has officially adopted mobile money technology for business purposes	1.308
Our employees know how to process mobile money payments	1.387
Our employees know that mobile money is acceptable in the firm	1.347
Our customers are able to make payment with mobile money	1.198
We are able to pay our suppliers with mobile money	1.091

Note: VIF<=5 is acceptable (Hair et al., 2014). Source: Field Data (2018)

4.6 Structural Model

The structural model examines the construct relationships within the context of the conceptual framework or hypotheses/propositions to be tested. This study examines the relationships between the higher-order constructs (independent variables) and firm-level adoption. Since the structural model involved higher-order constructs, the following procedures were applied based on recommendations by Hair et al. (2016) and Becker, Klein, and Wetzels (2012).

Personal factors were measured using six constructs. Personal factors were modeled as a reflective-formative type II construct (Becker, Klein, & Wetzels, 2012) with the six first-order reflective indicators. Firm internal factors were measured using six first-order constructs. Firm external factors were measured using three first-order constructs. General firm-level factors were modeled as a reflective-formative type II construct (Becker et al., 2012) with nine first order reflective indicators. Societal factors were measured using six constructs. Societal factors, thus, were modeled as a reflective-formative type II construct (Becker et al., 2012) with six first-order reflective indicators. Technological characteristics were measured using four constructs. Technological characteristics were modeled as a reflective-formative type II construct (Becker et al., 2012) with six first-order reflective indicators.

A correlation matrix of the five high-order constructs (Table 4) shows significant (strong) positive correlations between firm adoption, personal factors, firm-level factors, societal level factors and technology characteristics ($p<0.01$ in all cases). Even though some of the indices are closer to 0.8, several authors argue that correlation values alone are not conclusive to establish multicollinearity. Further analysis such as Variance Inflation Factors, tolerance, collinearity, and conditional indices are additional analysis that could be used to check for correlianity (Hair et al., 2014; Hair et al., 2016). The results show that all the variance inflation factors (VIFs) are lower than 5, which is recommended to prove the absence of collinearity problems (Hair et al., 2014). Therefore, the five high-order construct model does not present a collinearity problem.

Table 4. Correlation Matrix for Second/High-order Constructs

High Level Constructs	1	2	3	4	5
Firm-level Adoption	1				
Personal Level Factors	0.368***	1			
Firm Level Factors	0.278***	0.776***	1		
Societal Level Factors	0.246***	0.617***	0.733***	1	
Technology Characteristics	0.276***	0.334***	0.416***	0.592***	1

*Note: ***Correlation is significant at 0.01 level of significance. Source: Field Data (2018)*

4.7 Assessment of the Predictive Relevance *Q*-square

The structural model explains 21% of the variance for firm adoption, i.e., the main criterion or outcome construct (R^2 = .206), which is considered moderate. The explained variances for all the other endogenous constructs are included in Table 5. The present study also assessed the model's predictive power, using the Stone-Geisser's (Q^2) cross-validated redundancy, a blindfolding procedure in PLS, setting omission distance of 7 as a criterion for predictive relevance (Hair et al., 2016; Chin, 2010). Q^2 measures the predictive relevance of a model. The general rule of thumb is to have Q^2 value above 0 to show predictive relevance (Hair et al., 2016; Chin, 2010). The Q^2 -values obtained for the structural model is likewise presented in Table 5. Q^2 values of 0.06, 0.69, 0.37, and 0.34 were obtained for adoption, firm-level factors, personal level factors, and societal factors all of which are greater than 0 showing predictive relevance (Hair et al., 2016; Chin, 2010).

Table 5. Predictive Power of F-TAM Constructs

Constructs	R^2	Q^2	Firm Adoption	Firm Level Factors	Personal Level Factors	Societal Level Factors
Firm Adoption	0.206	0.059				
Firm Level Factors	0.707	0.686	0.01 (None)			
Personal Level Factors	0.382	0.372	0.11 (Small)	0.58 (Large)		
Societal Level Factors	0.350	0.342	0.01 (None)	0.259 (Medium)	0.44 (Large)	
Technology Factors	_	_	0.02 (Small)	0.00 (None)	0.00 (None)	0.54 (Large)

Note: Predictive Accuracy (R^2), Predictive Relevance (Q^2) and Effect Sizes (f^2), Source: Field Data (2018)

Table 6 provides a summary of the hypotheses test and conclusions made in this study. Of the nine study hypothesis, five are supported by the data.

Table 6. Summary of Hypotheses Assessment

Propositions	Definition	Standard Beta	Bootstrap t-value	Hypothesis results
P1	Personal level factors lead to firm adoption	0.480***	4.900	Supported
P2	Personal level factors influence firm factors	0.524***	12.190	Supported
P3	Firm factors lead to firm adoption	-0.029	0.229	Not Supported
P4	Societal level factors influence personal level factors	0.646***	14.265	Supported
P5	Societal level factors influence firm level factors	0.410***	7.633	Supported
P6	Societal level factors lead to firm adoption	-0.131	1.141	Not Supported
P7	Technology characteristics influence employee factors	-0.049	0.950	Not Supported
P8	Technology characteristics influence firm level factors	-0.001	0.029	Not Supported
P9	Technology characteristics influence societal factors	0.592***	14.660	Supported

*Note: ***Significant at $p<0.01$; **Significant at $p<0.05$;*Significant at $p<0.10$*

The hypotheses test results are explained as follows:

***H1**: Personal level factors lead to firm adoption.* The data showed a positive and significant relationship between personal level factors and firm adoption of mobile money innovations (β=0.480, t=4.900, p<0.01). Therefore, hypothesis 1 (*H1*) is supported in the present context. These outcomes suggest that the attitudes and perceptions of employees in a firm (SME) towards mobile money innovation, drive adoption of mobile money innovations, confirming a proposition of Doe et al. (2018).

***H2**: Personal level factors lead to firm factors*. The data showed a positive and significant relationship between personal level factors and firm-level factors (β=0.524, t=12.19, p<0.01). Therefore, hypothesis 2 (*H2*) is supported in the present context. This outcome means employees' attitudes and perceptions in a firm (SME) drive firm-level factors, confirming another proposition of Doe et al. (2018).

H3:** Firm factors lead to firm adoption*. The data showed that the relationship between firm-level factors and firm adoption of mobile payment innovations was not statistically significant (β=-0.029, t=0.229, p>0.05). Therefore, hypothesis 3 (H3)*** is not supported in the present context. This outcome means that firm-level factors do not necessarily drive adoption. This result contradicts a proposition of Doe et al. (2018) that suggested that firm factors will lead to firm adoption. A significant indication of the findings in hypothesis H1, H2, and H3 is that they challenge earlier models such as PERM model, TOE, and TTF that suggest that firm factors lead to firm adoption. Perhaps, if those studies had decoupled employee factors from other firm-level factors, the results of those studies would have been different. This finding underscores the essence of the F-TAM in examining the interrelationship between three levels of adoption as an eco-system, and decomposing employee factors from other firm level factors.

***H4:** Societal level factors influence personal level factors*. The data showed a positive and significant relationship between societal level factors and personal level factors (β=0.646, t=14.265, p<0.01). Therefore, hypothesis 4 (*H4*) is supported in the present context. This means societal level factors drive personal level factors, confirming another proposition of Doe et al. (2018).

***H5:** Societal level factors influence firm-level factors*. The data showed a positive and significant relationship between societal level factors and firm-level factors (β=0.410, t=7.633, p<0.01). Therefore, hypothesis 5 (*H5*) is supported in the present context. This outcome suggests that societal level factors drive firm-level factors, confirming another proposition by Doe et al. (2018).

***H6:** Societal level factors lead to firm adoption*. The relationship between societal level factors and firm adoption of mobile money innovations was not statistically significant (β=0.131, t=1.141, p>0.05). Therefore, hypothesis 6 (*H6*) is not supported in the present context. This outcome means societal level factors do not necessarily drive adoption. Juxtaposing this finding with *H1,* the evidence demonstrates that societal level factors rather drive personal level factors, which subsequently drive adoption. This finding contradicts a proposition of Doe et al. (2018) that societal factors will drive firm adoption. It also contradicts propositions in other models such as the Culture, Policy and Technology framework (Bajaj & Leonard, 2004) suggesting that policy issues, constructed in F-TAM under societal factors will lead to firm adoption.

***H7:** Technology factors influence employee factors.* The relationship between technological factors and personal/employee factors was not statistically significant (β=-0.049, t=0.950, p>0.05). Therefore, proposition 7 (*P7*) is not supported in the present context. This means technological factors do not necessarily influence personal/employee factors as contrarily suggested by Doe et al. (2018).

***H8**: Technology factors influence firm-level factors.* The relationship between technological factors and firm level factors was not statistically significant (β=-0.001, t=0.029, p>0.05). Therefore, proposition 8 (*H8*) is not supported in the present context. Again, this means technological factors do not necessarily drive firm-level factors, as contrarily suggested by Doe et al. (2018).

***H9**: Technology factors influence societal factors.* The data showed a positive and significant relationship between technological factors and societal level factors (β=0.592, t=14.660, p<0.01). Therefore, proposition 9 (*H9*) is supported in the present context. This result means technological factors drive societal level factors, confirming another proposition by Doe et al. (2018).

A pictorial view of the direct relationships supported by the data, in addition to suspected moderating relationships are shown in figure 1 below.

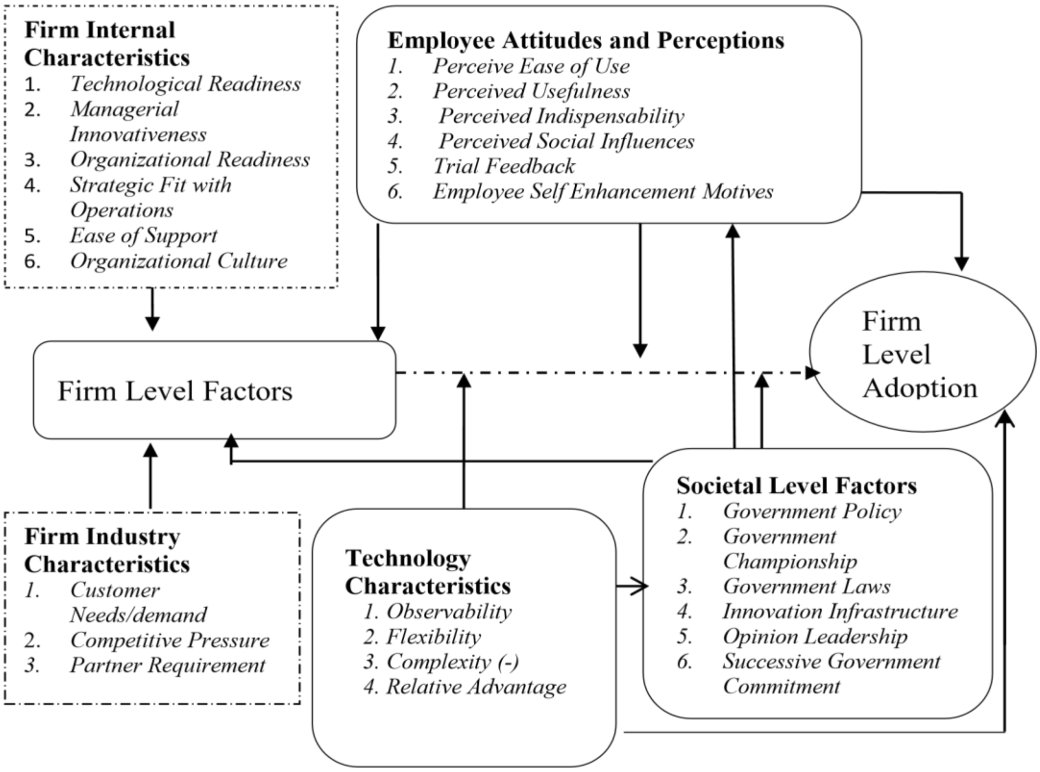

Figure 1. Survey Tested Technology Adoption Model (F-TAM)

4.8 Additional Study Observations

A substantially unexpected result from this study was the fact that firm-level factors do not necessarily lead to firm adoption. The results triggered the inquiry into further relationships that were hitherto, not posited, or anticipated earlier in this study. The data suggest a direct influence of technology characteristics on firm adoption as well as possible mediational effects of personal and societal factors. Likewise, we discovered that technological characteristics moderate the relationship between firm-level factors and firm adoption.

This study discovered that a positive and significant association exists between technological characteristics and firm adoption (β=0.165, t=1.984, $p<0.05$). This outcomes suggests that technological characteristics drive firm adoption, confirming Rogers' (1962) diffusion theory as still being relevant in the adoption of any innovation. This study discovered that technological factors moderate the relationship between firm-level factors and firm adoption (β=0.12, t=2.242, $p<0.05$). Thus, even though firm factors did not lead to firm adoption, the relationship between firm-level factors and firm adoption is strengthened by technological factors. This particular finding is another novel discovery in adoption studies. Earlier firm level models such as PERM, TTF, and TOE did not anticipate or conceive the idea of a possible strengthening of this relationship by technology characteristics.

Next to the observation on technology characteristics effect on the eco-system, we discovered some remarkable mediation effects. First, if personal level factors lead to firm adoption, and societal factors influence personal level factors, then personal level factors mediate the relationship between societal level factors and firm adoption. We observe that personal factors fully mediate the relationship between societal factors and firm adoption. Therefore, contrary to hypothesis 6 (H6), societal factors do have an indirect effect on firm adoption.

Secondly, if societal level factors lead to firm level factors, and societal level factor itself is influenced by technology characteristics, then we observe that **s**ocietal level factors mediate the relationship between technological characteristics and firm-level factors. Therefore, contrary to hypothesis 8 (H8) of this study, technological characteristics have a significant indirect effect on firm-level factors through societal level factors.

Finally, we found that **s**ocietal level factors fully mediate the relationship between technological factors and personal factors. This implies that technological characteristics have a significant indirect effect on personal factors through societal level factors. Therefore, contrary to hypothesis 7 (H7) of this study, which proposes a direct effect of technological characteristics on personal factors, the effect is an indirect one.

5. SUMMARY AND CONCLUSION

This paper sought to test the F-TAM, with associated hypotheses, using data collected from Ghanaian SMEs. The hypotheses were tested using PLS-SEM. The study found a positive and significant relationship between personal factors and firm adoption, personal factors and firm-level factors, societal level factors and personal factors, societal level factors and factors on the firm-level, technological factors and societal level factors, and technological factors and firm adoption. An unimagined result realized that firm-level factors do not necessarily lead to firm adoption, highlighting the need for re-examination of the link between firm factors of adoption and actual adoption.

Furthermore, societal level factors, personal factors, and technological factors were all found to moderate the association between firm-level factors and firm adoption. Thus, even though the link relationship between firm factors and firm adoption was insignificant, it is still relevant in the model. As a result, five of the nine hypotheses of the study are supported in the present context. It is important to note that, if this study had examined the effect of firm-level factors alone on adoption, we would have found significant relationships similar like previous studies. However, disaggregating personal level factors exposes the flaw in that idea. The study found a mediating effect of personal level factors on the relationship between societal level factors and adoption, a mediation effect of societal factors on the relationship between technology factors and firm-level factors, and between technology factors and personal factors.

6. THEORETICAL CONTRIBUTION AND PRACTICAL IMPLICATIONS

Our findings confirm most of the hypothesis in the revised F-TAM version (Doe et al., 2018), at the same time challenging some propositions in other models such as the CPT, PERM, and TOE models. Striking revelations from this study that calls for further studies include the following.

While employee factors can lead to firm adoption, firm factors of adoption, mainly posited by models such as the TOE, PERM model and TTF, do not lead to adoption if societal factors, characteristics of the innovation, and employee factors do not moderate that relationship. Societal factors do not lead to firm adoption if employee factors do not mediate this relationship. These findings make employee factors probably the most significant construct in the pool of factors that engender adoption. The findings seem to challenge all models that posit that firm factors alone will lead to firm adoption. Studies that classify employees as part of the firm factors may not face this challenge.

Irrespective of government efforts concerning laws, discussions, policies, and championships made towards the adoption of an innovation, innovation will not generally be adopted if employees are not at the center of the adoption drive. Technology factors do not influence employee factors. Thus, innovation could be flexible, easy to use, give some advantages and be easy to observe. However, if its employees do not perceive the innovation as such through the lenses of the employee factors, particularly self-enhancement motives, the innovation may not be adopted. These findings may challenge models such as the DOI, which is silent on the role of employees.

This study is theoretically relevant because the study challenges the concept that any particular level of factors will lead to adoption, without reference to the adoption eco-system. Thus, for firm adoption, all dimensions of factors must be aggregated before the real factors that engender adoption can be uncovered. Constructs confirmed in other models include technology characteristics in TTF, organizational characteristics in DOI, PERM, and TOE, societal factors in PERM and TOE. Our current contribution with the F-TAM, therefore, is a significant departure from earlier models. For industry practitioners, these findings illustrate the essence of putting a premium of recruiting technologically savvy employees if the firm intends to adopt digital technologies.

7. LIMITATIONS

This study has some limitations that future research should seek to address. First, this study employed purposive sampling (Straits & Singleton, 2017) in data collection in order to reach small firms that have adopted and used mobile payment technology innovation. The downside of this sampling technique is that studies that employ this technique do not generally lend themselves to a statistical representation of the whole population. Given that the initial adopters of new technologies tend to be technology-savvy and, in most of the firms, the owner-managers lead the adoption, the findings of this study may appear to be more tailored to savvy SMEs technologically. The results may, therefore, have some minor variations for SMEs who are not technologically savvy. Again, the adoption is assumed to be a voluntary adoption process as opposed to mandatory adoption. For instance, in several government championships and policy drives, there are issues of mandatory adoption imposed on adopters. When this model is applied to SMEs who may have adopted out of mandatory adoption, varied results may be reported under such circumstances. Secondly, we took samples from the capital of the Greater Accra Region, which is assumed to be the most developed region in Ghana. The generalizability of these findings on other regions may realize minor variations. Finally, this study is based on the F-TAM with firm adoption as the dependent variable. Although our results support the use of F-TAM in measuring the adoption of mobile digital innovations at the firm level, other satisfactory models can be applied to firm technology adoption. Any such model, however, must factor all four domains of the construct into the adoption equation. We recommend future studies with larger samples taken across the whole country and different countries. We also recommend the application of this model in mandatory adoption situations.

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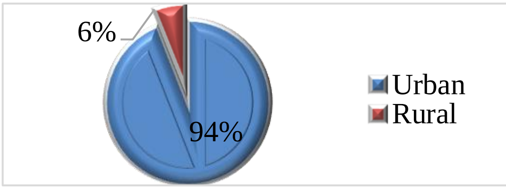
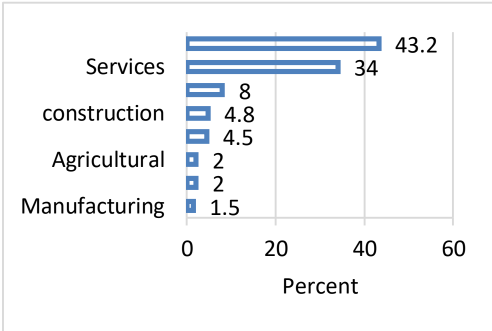
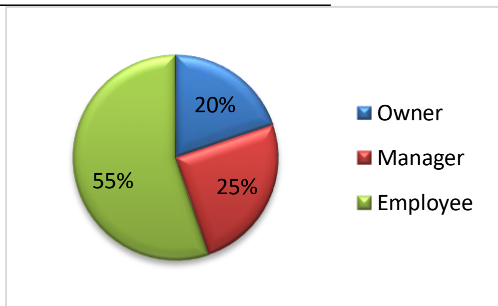
APPENDIX

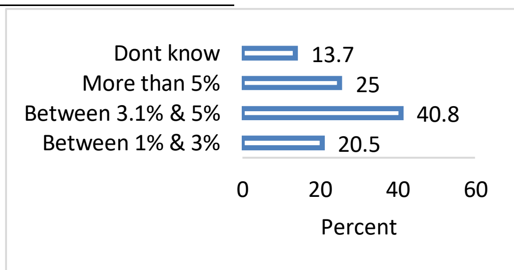
Table 4. SME Business Characteristics

Variables	Frequency (n)	Percentage (%)
Type of business location		
Urban	376	94.0
Rural	24	6.0
Total	**400**	**100.0**
Sector of Operation		
Food & Beverages	18	4.5
Manufacturing	6	1.5
Agricultural	8	2
Services	136	34
Fashion	32	8.0
Construction	19	4.8
Microfinance/Banking	8	2
Trading	173	43.2
Total	400	100.0
Position of Respondent		
Owner	79	19.8
Manager	100	25
Employee	221	55.2
Total	**400**	**100.0**
Percentage of Firm Budget Spent on Adoption		
Between 1% & 3%	82	20.5
Between 3.1% & 5%	163	40.8
More than 5%	100	25.0
Don't know	55	13.7
Total	**400**	**100.0**









Source: Field Data (2018)

Table 4.2. Business Characteristics-Descriptive

Variable	N	Minimum	Maximum	Mean	S.D
How long has your organization been in business (years)	383	2	25	6.45	4.196
Number of employees	385	1	103	9.66	16.726
Average turn over per year (GHC)	198	1000	774780	26584.6	57465.2
How long has your organization been using mobile money in your business	357	1	8	2.8207	1.45197

Source: Field Data (2018)