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John Otieno Oredo
Kisii University, john.oredo@gmail.com

James Njihia
University of Nairobi, muranga.njihia@gmail.com

XN Iraki
University of Nairobi, xniraki@gmail.com

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Research Paper

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John Oredo
Kisii University, Kenya
John.oredo@gmail.com

James Njihia
University of Nairobi, Kenya
muranga.njihia@gmail.com

XN Iraki
University of Nairobi, Kenya
xniraki@gmail.com

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ABSTRACT

While there is substantial literature on the adoption of IT innovations based on utility computing, there is a dearth of studies on cloud computing adoption by business organizations. Given that cloud computing adoption has been steadily increasing in Kenya, this study aim to investigate the determinants of cloud computing adoption from an institutional perspective. The relationship between institutional pressures and cloud computing adoption was evaluated and tested using structural equation modelling (PLS SEM). A firm level cross sectional survey was conducted on a sample of 93 firms in the financial, manufacturing, and ICT sectors. The results indicate that coercive and normative pressures have a significant positive relationship with cloud computing adoption. The hypothesis that mimetic pressures have a relationship with cloud computing adoption was not supported. A major implication of this study is that professional and standards bodies do influence technology adoption through normative pressures.

Keywords

Cloud computing adoption, institutional theory, mimetic pressures, coercive pressures, normative pressures, structural equation modelling.

INTRODUCTION

Cloud computing is an Information Technology (IT) innovation that allows users to temporarily utilize computing infrastructure over the network, which is supplied as a service by a cloud provider at possibly one or more levels of abstraction (Venters & Whitley, 2012). The utilization of IT resources as a service rather than as a products has attracted organizations due to its benefits, such as minimal upfront investment (Mather, Kumaraswamy, & Latif, 2009), flexibility, scalability (Zhang, Cheng, & Boutaba, 2010), speed of deployment, and access to quality software (Lee, Chae, & Cho, 2013). On the other hand, organizations still have concerns regarding security and privacy of data (Buyya, Goscinski, &

Broberg, 2011), the reliability and availability of cloud services (Buyya et al., 2011), vendor management (Ernst & Young, 2011), and regulatory ambiguity (KPMG, 2011). Despite the concerns, cloud computing adoption by organizations is on the rise, with Gartner predicting that the worldwide public cloud services market will grow by 16.5 percent in 2016 to a total of $204 billion, up from $175 billion in 2015 (Gartner, 2016). International studies on key IT and management developments ranked cloud computing at the second and third positions in 2011 and 2012 respectively (Luftman & Zadeh, 2011; Luftman et al., 2012). A similar study conducted in the year 2013 again ranked cloud computing in the second position (Luftman et al., 2013). These studies suggest that organizations are gradually recognizing the strategic value of cloud computing.

In addressing the need to understand IT innovations adoption, extant studies have mainly employed the economic-rational models (Fichman, 2004) and socio-cognitive models (Wang, 2009). The economic-rational models have recently been labelled as the “dominant paradigm” by Fichman (2004) because these models have dominated IT innovation research for the last two decades (Benbasat & Barki, 2007). In this study, theories of the economic-rational model are considered to include the diffusion of innovation theory (DOI) (Rogers, 1983), the technology acceptance model (TAM)(Davis, 1989), and the technology organization environment (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990). A common strand in these theories is that organizational factors determine the adoption of IT innovations and whether an organization will benefit from the adoption or not. According to the economic-rational models, an organization’s decision to adopt an IT innovation is determined by both technology and organizational contexts. It is assumed that organizations possessing an innovator’s profile - which include size, diversity, technical expertise and supportive senior management - will exhibit a greater quantity of innovation (Fichman, 2004). Regarding technology context, it is assumed that the attributes of a technology, (e.g., relative advantage, compatibility, triability, observability, and complexity [Rogers, 1983)]) determine an organization’s decision to adopt the innovation. Generally, the economic-rationalistic school posits that decision makers adopt an innovation because of the expected efficiency or returns (Fiol & O’Connor, 2003).

While the economic-rationalistic models have reasonably worked well in answering the questions they are intended to answer (Fichman, 2004), their linear discourse has been criticized as “over rationalized” and fails to provide plausible explanations for the institutional and technical complexities of modern organizational environments (Abrahamson, 1991). Furthermore, the economic-rationalistic models are seen as being pro-innovation and they adopt a perspective that privileges the new over the taken for granted, adoption over rejection and factor over process (Fidock & Carroll, 2010). According to Fichman (2004), the economic-rationalistic paradigm has accomplished high predictability, the paradigm itself “may be reaching the point of diminishing returns,” and IT innovation research should go beyond organizational boundaries. Furthermore, there is a need to theorize the IT artifact (Orlikowski & Iacono, 2001) as a multilevel product of local and trans-organizational forces acting in concert (Swanson & Ramiller, 2004). In order to step out of the organizational boundaries in IT innovation research, Fichman (2004, p. 315) and Wang (2009) proposed the socio-cognitive approach as a possible avenue. The social-cognitive perspective argues that the adoption and diffusion of IT innovation among organizations is socially constructed by technology discourse, as well as shared norms, values, and beliefs about the innovation (Yang & Hsu, 2011). The main socio-cognitive theories include institutional theory (Meyer & Rowan, 1977), power and trust (Hart & Saunders, 1997), organizing vision (Currie, 2004; Swanson & Ramiller, 1997), management fashion (Wang & Ramiller, 2004), and innovation concept (Wang, 2009).

In contrast to the economic-rationalistic models, the institutional theory, which is the socio-cognitive model adopted for this study, argues that structural and behavioral changes in organizations are determined less by competition and the desire for efficiency and more by the need of organizational legitimacy (Liang, Saraf, Hu, & Xue, 2007) within an institutional framework. Orlikowski and Barley (2001) note that the institutional theory offers IT researchers a vantage point for conceptualizing the digital economy as an emergent and provisional social production shaped as much by cultural and structural forces as by technical and economic ones. According to Teo et al. (2003), organizations face pressures to conform to practices and policies readily accepted as legitimate and rational means to attain organizational goals. The institutional theory explains that institutions exert three kinds of forces or pressures on organizations and organizational actors: mimetic, coercive, and normative pressures (DiMaggio & Powell, 1983). Due to mimetic pressures, organizations model themselves after other organizations deemed to be successful when faced with a new and poorly understood technology. Mimetic pressures may cause an organization to respond to uncertainty by mimicking the actions of other organizations (Liang et al., 2007). Coercive pressures are defined as formal or informal pressures exerted on organizations by organizations upon which they are dependent (DiMaggio & Powell, 1983). Coercive pressures stem from a variety of sources including resource dominant organizations, regulatory bodies, and parent organizations (Teo et al., 2003). Normative pressures occur primarily as a result of professionalization, which is a collective struggle of members to define and establish an occupational autonomy (DiMaggio & Powell, 1983).

There is some evidence that institutional pressures affect the adoption of IT innovations. For example, institutional pressures have significant influence on organizational intention to adopt the Federal Electronic Document Interchange (FEDI) (Teo et al., 2003) and Enterprise Resource Planning (ERP) (Benders, Batenburg, & van der Blonk, 2006). A study by Trope (2014) concluded that mimetic pressure is more important than coercive and normative pressures in the adoption of cloud computing by South African firms. While the institutional theory has been substantially used in explaining the organizational adoption of a number of previous IT innovations, it is still underutilized as a theoretical lens for understanding the organizational adoption of cloud computing. This study explores the role of institutional pressures in the organizational adoption of cloud computing by selected firms in the financial, manufacturing, and ICT sectors.

LITERATURE REVIEW

Cloud Computing

Cloud computing is a model for enabling ubiquitous, convenient, and on-demand network access to a shared pool of configurable computing resources (networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (Mell & Grance, 2011cited in Venters & Whitley, 2012). Cloud computing allows for the utilization of computing resources as services over the internet without the users having to necessarily own the computing resources.. In the course of cloud computing development, different classifications have been used to capture its service layers. These layers have been referred to as cloud service models (Sriram & Khajeh-Hosseini, 2010), cloud business models (Yang & Hsu, 2011), and cloud architectural layers (Stanoevska-Slabeva & Wozniak, 2010). The earliest classification of cloud service models known as the SPI model stratified cloud services into software as a service (SaaS), platform as a service (PaaS) and infrastructure as a service (IaaS) (Yang & Hsu, 2011). These cloud computing deployment models are classified based on two features: physical location and distribution; and the owner of the cloud data center (Buyya et al., 2011). Accordingly, there are three cloud deployment models: private, public, and hybrid (Buyya et al., 2011). The provision of IT as a Service (ITaaS) is possible due to the following characteristics of cloud computing: on-demand self-services, in which a consumer can unilaterally provision computing capabilities without the provider's intervention; broad network access; resource pooling by the service provider to be used when needed by consumers; and a measured service for which consumers are billed just like electricity consumption.

There are several compelling reasons for organizations to move operations toward cloud computing. Adoption of cloud computing requires very minimal upfront investment. Cloud services can also be rapidly allocated and de-allocated on demand (Zhang et al., 2010), thus lowering operating costs. Scalability of cloud computing allows organizations to demand computing resources and services as needed because cloud providers pool large amounts of resources that are easily accessible depending on individual demand. Services hosted in the cloud are generally web-based and are easily accessible through a variety of devices with internet connections (Zhang et al., 2010). Finally, cloud computing reduces business risks and maintenance expenses, which are passed on to the cloud service provider (Zhang et al., 2010).

Despite the benefits of cloud adoption, there are several challenges of a technical, managerial, and regulatory nature. Technical challenges include the availability and reliability of cloud services, a lack of sufficient tools for integration and componentization of the various elements of the cloud, and a limited scope for customization in order to suit the specific needs of an organization (Stanoevska-Slabeva & Wozniak, 2010). Managerial challenges to cloud computing arise from the fact that an organization has to deal with many service and infrastructure vendors, a situation that may lead to data security problems (Kim, 2009). The provision of infrastructure and services by a vendor raises the fear of vendor lock-in (Kim, 2009). Cloud users also face organizational inertia, as shifting to a cloud environment may change the role of IT departments in the organization and the way operations are carried out in general. Regulatory problems are due to the fact that cloud service providers and consumers may not be operating within the same legal or regulatory jurisdiction, which leads to compliance/regulatory ambiguity (Ernst & Young, 2011)

Financial, ICT and Manufacturing Firms in Kenya

Business enterprises in an economy are usually classified according to industry. Financial, ICT, and manufacturing are some of the industries in a typical economy. The three industries were selected for this study because they have been identified as early adopters of cloud computing globally with an average of 7.24 cloud apps adopted per business unit amongst them, compared to an average of 5.4 for all other industries combined (TATA Consultancy Services, 2012). A study done in South Africa also indicates that the ICT sector was leading in cloud computing adoption at 54% followed by manufacturing sector at 47% and the financial sector at 33% (Trope, 2014).

The adoption of cloud computing in Kenya is still emerging. A cloud computing in Kenya report indicates that adoption of cloud computing is fairly recent with first adopters appearing in 2010 (Omwansa, Waema, & Omwenga, 2014). Since Kenya has been the finest in ICT innovation in Africa and home to multiple regional hubs including IBM's first African research lab and Google's first sub-Saharan African office (ICT Authority, 2014), it is well positioned for cloud computing adoption. The report by Omwansa et al. (2014) confirms this in stating that 90% of respondents thought that the cloud services market is ready in Kenya. The report further states that 48% of small and medium enterprises in

Kenya have adopted cloud computing, with a further 28% planning to adopt in the near future. Enterprises and institutions in the financial, ICT, and manufacturing sectors are expected to be amongst the 48% of early adopters. In Kenya, the finance sector has 43 banking and mortgage institutions, 13 microfinance institutions (CBK, 2017), and 71 insurance companies (IRA, 2017). The ICT sector is the largest among the three with a total of 1,278 firms ("Communications Authority of Kenya," 2018). Lastly, there are 627 large scale manufacturing firms in Kenya (KAM,2018).

The Institutional Theory

An institution is a social structure made up of a collection of individuals or organizations within which collectives exercise action or orientations in a constrained environment that will continuously be altered over time (Meyer & Rowan, 1977). The institutional theory posits that structural and behavioral changes in organizations are determined less by competition and the desire for efficiency and more by a need of organizational legitimacy (Liang et al., 2007). According to Teo et al.(2003), organizations face pressures to conform to practices and policies readily accepted as legitimate and rational means to attaining organizational goals. The institutional perspective has been used by various researchers to explain why certain organizational structures and ideals endure, and to study the internal and external influences on organizational patterns (Weerakkody, Dwivedi, & Irani, 2009). Institutional pressures are one of the processes examined by the institutional theory (Japperson, 1991). Institutions exert three kinds of institutional pressures on organizations and organizational actors: mimetic, coercive, and normative pressures (DiMaggio & Powell, 1983).

According to DiMaggio and Powell (1983), mimetic pressures may cause an organization to change over time to become more like other organizations in its environment. Mimetic pressures often appear at times of uncertainty, when firms will tend to model themselves on other organizations in their fields perceived to be more legitimate or successful (DiMaggio & Powell, 1983). It is possible for an organization to mimic or imitate the actions and behaviors of other structurally similar organizations in the environment where the organization exists (Trope, 2014). Several factors contribute to mimetic behavior by organizations. First, organizations may manifest mimetic behaviors in order to model themselves after other organizations in a bid to acquire status-conferring legitimacy or social fitness in a wider social structure (DiMaggio & Powell, 1983). The urge for legitimacy may lead an organization to adopt an IT innovation regardless of its technical or economic efficiency. The second factor that contributes to mimetic behavior is uncertainty. In cases where the uncertainty of returns from a managerial initiative is ambiguous and difficult to quantify - regardless of whether or not this initiative is an IT innovation or administrative change - an organization may simply model itself on other organizations in an effort to pursue easy and affordable imitation (Ravichandran, Han, & Hasan, 2009). Given that organizations are still uncertain of the outcomes of cloud computing adoption, an organization may copy other organizations' successful efforts to implement information systems (Liang et al., 2007). A study by Teo et al. (2003) investigating the role of institutional forces in the adoption of FEDI found that organizations tend to imitate structurally similar firms perceived as successful. Another study conducted on cloud computing adoption by South African firms also concluded that greater mimetic pressures will lead to greater adoption of cloud computing (Trope, 2014, p. 92). Thus, consistent with Liang (2007), Teo et al.(2003) and Trope (2014), we propose the hypothesis:

> H1: There is a relationship between mimetic pressures and cloud computing adoption by Financial, ICT and Manufacturing firms in Kenya

Coercive pressures are defined as a formal or informal pressures exerted on organizations by other organizations upon which they are dependent (DiMaggio & Powell, 1983). Empirical evidence suggests that coercive pressures on organizations are built into exchange relationships and may stem from a variety of sources including suppliers, customers, resource dominant organizations, regulatory bodies, and parent corporations (Teo et al., 2003; Yigitbasioglu, 2015). A dominant actor controlling scarce and important resources may demand that organizations dependent on it adopt structures or programs that serve its interests, and that these resourced-dependent organizations may comply in order to secure their own survival (Pfeffer and Salancik, 1978 cited in Teo et al., 2003). It has been shown that coercive pressures have significance in the adoption of innovations in the form of institutionalized interdependency. Institutionalized interdependency is manifested across organizations within an industry or environment, as such organizations are likely to exhibit similar structural features (Liang et al., 2007). Furthermore, organizations that share the same environment tend to take on similar forms as efficiency-seeking organizations seeking the optimal ‘fit’ with their environment (Mignerat & Rivard, 2009). Extant literature has noted that a lack of government regulations can hinder enterprises from adopting cloud computing (Lian, Yen, & Wang, 2014; Luoma & Nyberg, 2011; Nkhoma & Dang, 2013). Hence we hypothesize:

> H2: There is a relationship between coercive pressures and cloud computing adoption by Financial, ICT and Manufacturing firms in Kenya

Lastly, normative pressures are brought about by professionalization resulting from inter-organizational networks, similar educational backgrounds, and mimetic behaviors in a profession (DiMaggio & Powell, 1983). Relying on social contagion literature, Burt (1987) contends that a focal organization with direct or indirect ties with other organizations that have adopted an innovation is able to learn about that innovation and its associated benefits and costs, and is likely to be persuaded to behave similarly. The inter-organizational learning that leads to normative pressures happens through relational channels amongst members of a network which further facilitates consensus which in turn increases the strength of these norms and their potential influence on organizational behavior (Powell & DiMaggio, 1991). Normative pressures are known to arise from dyadic relations which enable focal organizations with direct or indirect ties to other organizations to learn from through the sharing of information, norms, and rules (Soares-Aguiar & Palma-dos-Reis, 2008). In the context of IT innovation adoption, the normative pressures that an organization faces regarding the adoption of cloud computing are heightened by factors such as cloud computing adoption by its suppliers and customers, participation in professional bodies, and trade or business organizations that endorse the adoption of cloud computing (Trope, 2014). Therefore, the following hypothesis is suggested:

> H3: There is a relationship between normative pressures and cloud computing adoption by Financial, ICT and Manufacturing firms in Kenya

RESEARCH METHODOLOGY

Research Design

The study used a cross-sectional survey to gather data from the respondents. The cross-sectional survey has been found to be robust for effects of relationship studies in previous information systems studies such as Teo et al. (2003), Liang et al. (2007), and Wolf et al.(2009). A cross-sectional study is appropriate when the overall objective is to establish whether significant associations exist among variables at some point in time. Since this study has a priori model, the survey method is suitable as it provides a basis for establishing generalizability, replicability, and statistical power (Teo et al., 2003). On the explanatory aspect, the study examined the relationship amongst institutional forces and cloud computing adoption by way of hypothesis testing. A model to capture the relationship was developed using the partial least squares structural equation modelling (PLS-SEM). PLS-SEM is a single systematic statistical technique for testing and estimating causal relationships amongst latent variables (Urbach & Ahlemann, 2010). PLS- SEM was chosen for this study because it is considered more appropriate for exploratory research and shares the modest distributional and sample size requirements of ordinary least squares regression (Chin, 2010). Further, PLS-SEM has been extensively applied in information systems research. In a study on the use of PLS-SEM in Management Information Systems Quarterly (MISQ), out of the 109 SEM based articles published from 1999 through to 2011, 65 (60 percent) of the articles applied PLS-SEM (Ringle, Sarstedt, & Straub, 2012).

Model Development

The purpose of the study was to analyze the causal relationship between institutional pressures and cloud computing adoption. A priori model was constructed using PLS-SEM to embody the relationship between the study variables. A PLS-SEM model consists of the structural model and a measurement model (Urbach & Ahlemann, 2010). The structural model embodies the relationship between the latent variables. The structural model we developed for this study was guided by the institutional theory. The sub-constructs of the institutional theory comprising mimetic pressures, coercive pressures, and normative pressures were used as the exogenous latent variables while cloud adoption was used as the endogenous latent variable. Each of the latent constructs of institutional pressures was estimated using four second order formative indicators as part of the measurement model. Even though the use of reflective indicators is considered the norm for PLS-SEM studies (Urbach & Ahlemann, 2010), we opted to use formative indicators following Teo et al. (2003). The latent variable of cloud computing adoption was estimated as a second order reflective variable. This choice was influenced by the fact that the SmartPLS 3 implementation of PLS-SEM requires that at least one latent variable be estimated as a reflective variable.

Extant literature on institutional based theories was examined for the validated indicators for mimetic pressures, coercive pressures, and normative pressures. The measures were then adapted to suit the specifics of the study. The mimetic pressures construct was operationalized in terms of the extent of IT innovation by a firm’s competitor and the perceived success of the firm that had adopted the IT innovation (Liang et al., 2007). The measures for coercive pressures were operationalized around the influence of the government, industry associations, and parent companies in promoting the adoption of an IT innovation (Liang et al., 2007; Teo et al., 2003). According to Rawski (1994), coercive pressures are likely to arise from governments and collective industry associations. Finally, normative pressures were perceived to arise from members of dyadic relational channels and multilateral organizations like professional, trade, and industry associations (Mignerat & Rivard, 2009; Teo et al., 2003). Cloud computing adoption was captured by asking the respondents if they had adopted any of the cloud computing offerings in the areas of Software as a Service (SaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). A summary of how the indicators were operationalized is presented in Table 1.

Latent Variables	Indicators	Literature
Mimetic Pressures	Competitors who have adopted cloud computing have mainly benefited (MP1).	(Liang et al., 2007; Teo et al., 2003)
	Competitors who have adopted cloud computing are favorably perceived by others in the industry (MP2).	
	Competitors who have adopted cloud computing are favorably perceived by customers (MP3).	
	Competitors who have adopted cloud computing are favorably perceived by suppliers (MP4).	
Coercive Pressures	Government requires organizations to adopt cloud computing (CP1).	(Liang et al., 2007; Rawski, 1994; Teo et al., 2003)
	Industry organizations require members to adopt cloud computing (CP2).	
	Competitive conditions pressure firms to adopt cloud computing (CP3).	
	Parent organization requires all subsidiaries to adopt cloud computing (CP4).	
Normative Pressures	Extent of cloud computing adoption by firm's suppliers (NP1).	(Liang et al., 2007; Mignerat & Rivard, 2009; Teo et al., 2003)
	Extent of cloud computing adoption by firm's customers (NP2)	
	Extent to which government promotion of cloud computing has influenced a firm's adoption (NP3).	
	The extent to which membership in trade and professional organizations have influenced a firm's adoption of cloud computing (NP4).	
Cloud Computing Adoption	Adoption of Software as a Service (SaaS) (CCA1)	(Ahson & Ilyas, 2011; Yang & Hsu, 2011; Zhang et al., 2010)
	Adoption of Platform as a Service (PaaS) (CCA2)	
	Adoption of Infrastructure as Service (IaaS) (CCA3)	
	Adoption of Communications as a Service (CaaS) (CCA4)	
	Presence of remote data centers owned by the firm (CCA5)	
	Utilization of remote virtualized resources (CCA6)	

Table 1:The Operationalization of the Latent Constructs

The combination of the structural model and the measurement model leads to a complete structural equation model. The research model embodies both the measurement and the structural models of this study. The measurement model shows the relationship between the empirically observable indicator variables and the latent variables (Urbach & Ahlemann, 2010). The structural model represents the causal relationships in terms of paths where each path (e.g., H1, H2 and H3) is a hypothesis for testing a theoretical proposition (Lowry & Gaskin, 2014). The research model is represented by Figure 1.

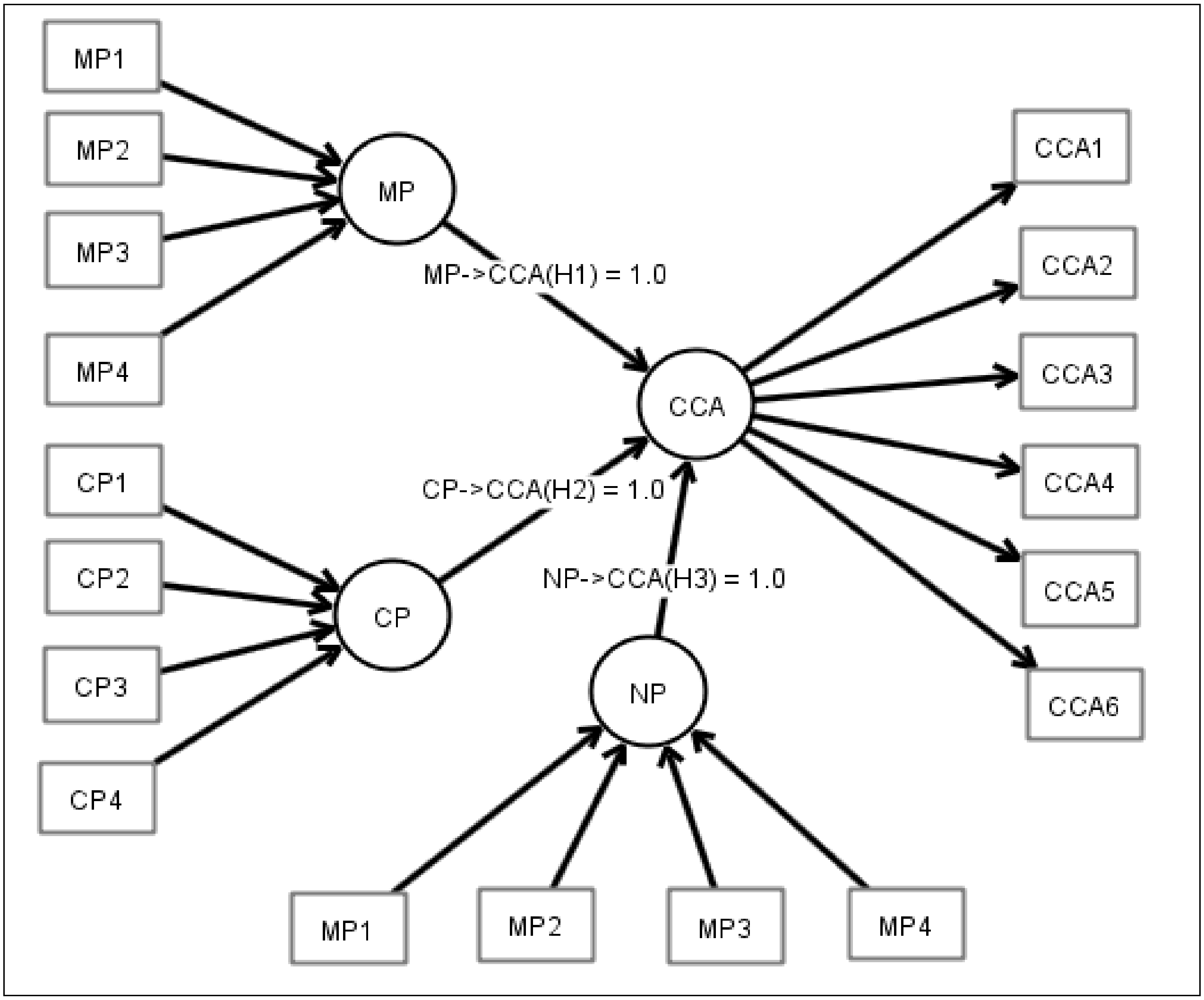

Figure 1: The Research Model

Population, Sampling and Data Collection

The population of the study referred to firms in the financial, manufacturing, and ICT sectors registered in Kenya. The firms in the financial sector were identified from both the Central Bank of Kenya website (CBK, 2017) and the Insurance Regulatory Authority website (IRA, 2017), as there is no single database listing all the firms in the financial sector. There are a total of 153 licensed firms in the financial sector with 56 of them being in the banking sector and 97 firms in the insurance sector. The firms in the ICT sector were identified from the list of licensed organizations in this sector available on the Communications Authority (CA) of Kenya website ("Communications Authority of Kenya," 2018). The firms in the ICT sector are categorized in terms of the services they offer. This study selected firms from the category of content service providers, which provides a representative list of firms in the sector. According to CA, there are 221 licensed content service providers from a total of 1,278 licensed firms in the ICT sector. In the manufacturing sector, a population of 627 large manufacturing firms formed part of the population. The large manufacturing firms were identified from the Kenya Manufacturing Association's handbook (KAM, 2011).

A random sample of 60 firms from each sector was selected for the study. The choice of the sample size was guided by the N:q ratio where N represents the number of cases and q represents the number of model parameters (Jackson, 2003). According to Kline (2010), the recommended ratio for structural equation modelling (SEM) study is 20:1. In this study, there are three model parameters to be estimated as shown in Figure 1 (NP->CCA, CP->CCA and NP->CCA). Therefore, the required minimum sample size is 60. An additional 120 firms were added to the recommended minimum sample size to take care of possible non-responses. Out of the 180 questionnaires that were sent to respondents, 97 responses were received, leading to a response rate of 53.8 percent. On examination of the completeness of the questionnaires, 15 were found to be incomplete. 4 of the 15 incomplete questionnaires were discarded as the respondents only filled the demographic items, which comprised 40 percent of the total questionnaire items. The remaining 11 incomplete questionnaires were used as the respondents had answered most of the questions. The questionnaires may have not been completed due to several factors: a perceived confidentiality of data, a lack of understanding, or a reluctance of the respondents to answer a question that they thought was irrelevant to their business operations. To complete the missing values, a sub-group mean value replacement function was used (Kaiser, 2014). After completing the missing values, the 93 questionnaires became usable. The response rates by industry are shown in Table 2.

Industry	Mailed	Response	Response Rate(Industry)	Response Rate(Overall)
Financial	60	33	55%	18.3%
ICT	60	49	82%	27.2%
Manufacturing	60	11	18%	6.1%
Total	180	93		51.6%

Table 2: Response Rate by Sector

The questionnaire instrument was administered online to the managers having ICT-related responsibilities in each of the sampled firms. The sampled firms were reached through their official landline or mobile phone numbers. Each firm was then asked to provide the researcher with the email address of any of its managers with ICT-related responsibilities. The ICT managers were then requested to act as respondents on behalf of the firm. The ICT managers were selected not only because they are boundary spanning (Tushman & Scanlan, 1981), but because they are also considered opinion leaders during IT innovation adoption decision processes within their firms (Rogers, 1995). The web-based questionnaire was designed using Survey Monkey® which is an online survey tool. The questionnaire was then sent to the respondents as a link through their email addresses. Though internet-based surveys are similar to surveys with mail questionnaires, the former are considerably faster (Tse, 1998) and more cost-effective (Sheehan & McMillan, 1999). Additional advantages of email and web-based questionnaires over snail mail questionnaires is that they are environment friendly (Tse, 1998), allow multimedia content (Best & Krueger, 2002), and offer easier data translation (Healey, Baron, & Ilieva, 2002). In administering the web questionnaire, an initial email invitation was sent to the respondents. After the initial invitation, four rounds of reminders were sent out with different formulations of invitation text to improve the response rate as recommended by Sivo et al. (2006).

The unit of analysis was at the organizational level or the firm level. Since the purpose of the study was to understand the adoption of cloud computing by the firms, the respondents consisted of managers with ICT-related responsibilities. Prior research in management suggests that the perceptions of top management reflect the collective perspective of the organization and, therefore, the subjective opinions of top managers are held as reliable sources of firm level data (Pecotich, Purdie, & Hattie, 2003). Further, IT managers deal directly with technological and organizational issues on a daily basis and attempt to resolve those issues through well-informed choices on the capability and applicability of IT innovations (Ezell, 2015, p. 66). The respondents consisted of Chief Information Technology Officers, ICT Managers, Information Systems Managers, Chief Information Officers, and Information Security Managers. An "Others" option was included in the questionnaire to cater for ICT responsibilities not covered by the above titles.

DATA ANALYSIS AND RESULTS

Analysis Strategy

The hypotheses of the research model were tested based on empirical data by means of structural equation modelling with the support of the SmartPLS 3.0 software (Ringle, Wende, & Becker, 2015), which is based on partial least squares. Structural equation modelling is a type of second generation multivariate statistical analysis (Lowry & Gaskin, 2014) that has attracted great interest in IT research (Im & Grover, 2004; Urbach & Ahlemann, 2010). It was used to estimate the relationships amongst mimetic forces, coercive forces, normative forces, and cloud computing adoption. SEM was used in this study because it has potential advantages over regression analysis and because it is the method of choice when it comes to analyzing path diagrams that have latent variables with multiple indicators (Gefen, Straub, & Rigdon, 2011). SEM comes with the power to integrate the measurements (measurement model) and the hypothesized causal paths (structural model) into a simultaneous assessment. This process makes the estimation produced by SEM better than those produced by linear regression when the distribution assumptions hold (Gefen et al., 2011). The test of the research model involved assessing both the measurement (outer model) and the structural model (inner model).

Model Evaluation

Measurement Model Evaluation

The reliability and validity of the measurement model and the structural model were assessed at the indicator and the construct levels following Henseler et al. (2009). Reliability and construct validity were not assessed for the formative indicators since reliability and construct validity are not considered meaningful in the case of formative measurements (Bagozzi, 2007; Diamantopoulos, 2006). Straub and Boudreau et al. (2004) state that, "It is not clear that reliability is a concept that applies well to formative constructs." According to Diamantopoulos and Siguaw (2006, p.270) and Rossiter (2002,p.315), dimensionability and reliability tests are not conducted on formative indicators because factorial unity in factor analysis and internal consistency are not relevant. But Andreev, Heart et al. (2009) conclude that construct reliability of formative indicators should be performed by a test of multicollinearity with the assumption that multicollinearity should not exist (Diamantopoulos & Winklhofer, 2001). For the mimetic, coercive, and normative pressures whose measurements were specified as formative, multicollinearity was assessed through variance inflation factor (VIF). All the factors had a VIF of less than 10, which is considered a better threshold for non-multicollinearity (Diamantopoulos & Siguaw, 2006; Hair, Anderson, Tatham, & Black, 1995). The VIF estimates summary is presented in Table 3.

Cloud computing adoption (CCA) was specified as a reflective indicator. The indicator was evaluated in terms of its reliability and validity. Internal consistency reliability - which measures the degree to which the indicators load simultaneously when the latent variable increases - was evaluated using composite reliability (CA) with a threshold value of 0.700 and above (Hair, Ringle, & Sarstedt, 2011; Latan & Ghozali, 2012).

Construct Name	Code	Mean	S.D	VIF
Mimetic Pressures	MP1	0.795	0.192	1.745
	MP2	0.712	0.208	4.009
	MP3	0.704	0.215	3.806
	MP4	0.683	0.221	3.016
Coercive Pressures	CP1	0.575	0.245	2.075
	CP2	0.367	0.270	2.009
	CP3	0.548	0.421	1.319
	CP4	0.748	0.178	1.600
Normative Pressures	NP1	0.567	0.230	1.594
	NP2	0.871	0.120	1.440
	NP3	0.251	0.259	1.583
	NP4	0.405	0.237	1.600

Table 3: Reliability Test of Mimetic, Coercive, and Normative Pressures

Convergent validity was assessed using the average variance extracted (AVE). The AVE measures the amount that latent variable component captures from its indicators relative to measurement error and the recommended threshold value is above 0.500 (Hair et al., 2011; Latan & Ghozali, 2012). The indicator reliability which measures how much of the indicators variance is explained by the corresponding latent variable was evaluated using cross loadings with a threshold value of 0.700 or slightly lower for exploratory studies (Chin, 1998). The values for CA, AVE, and the cross loadings CCA is summarized in Table 4.

Latent Variable	Items/Indicators	Indicator Reliability	CA	AVE
CCA	CCA1	0.884	0.891	0.593
	CCA2	0.799		
	CCA3	0.876		
	CCA4	0.855		
	CCA5	0.319		
	CCA6	0.733		

Table 4: Indicator reliability, internal consistency and convergent validity assessment

Lastly, the discriminant validity was also evaluated. With discriminant validity, cross loadings are obtained by correlating the component scores of each latent variable with all other items and should show that the loading for each indicator is highest for its designated construct than for any of the other constructs (Chin, 1998; Latan & Ghozali, 2012). All of the indicators met the requirement for discriminant validity as shown in Table 5.

INDICATORS	CCA	CP	MP	NP
CCA1	0.884	0.336	0.314	0.404
CCA2	0.799	0.211	0.339	0.237
CCA3	0.876	0.28	0.36	0.404
CCA4	0.855	0.297	0.262	0.316
CCA5	0.319	0.203	0.092	0.203
CCA6	0.733	0.241	0.096	0.264
CP1	0.242	0.699	0.102	0.14
CP2	0.158	0.456	0.24	0.266
CP3	0.218	0.631	0.398	0.304
CP4	0.3	0.866	0.203	0.42
MP1	0.314	0.129	0.924	0.379
MP2	0.277	0.363	0.816	0.412
MP3	0.276	0.357	0.813	0.45
MP4	0.271	0.329	0.796	0.402
NP1	0.266	0.462	0.447	0.646
NP2	0.402	0.309	0.411	0.976
NP3	0.127	0.328	0.218	0.307
NP4	0.194	0.294	0.277	0.471

Table 5:Cross Loadings to Assess Discriminant Validity

Structural Model Evaluation

Following the successful evaluation of the measurement (outer) model evaluation, the structural (inner) model was analyzed. The first criterion to be analyzed was the relationship between each of the latent variables' explained variance to its total variance using the coefficient of determination (R^2) criterion. The values should be sufficiently high for the model to have a minimum level of explanatory power (Urbach & Ahlemann, 2010). The acceptable R^2 according to a rough rule of the thumb is 0.750, 0.50, and below 0.25, respectively describing substantial, moderate, or weak levels of predictive accuracy (Hair et al., 2011; Henseler et al., 2009). The R^2 for the structural model was 0.237, indicating a weak explanatory power. The path coefficients between the model's latent variables were then checked for algebraic signs, magnitude, and significance. All the path coefficients were more than 0.100 and therefore accounted for a certain level of impact within the model (Urbach & Ahlemann, 2010). Further, the path coefficients were examined for significance at 10% and 5% following Latan and Ghozali (2012). The significance levels were determined using the bootstrapping technique (Helm, Eggert, & Garnefeld, 2010). The bootstrapping algorithm employed 500 subsamples and generated the T-statistics and p-values after running 300 iterations as shown in Table 5. The path coefficient for the relationship between CP and CCA had a significance level of 10%, while that of NP and CCA was significant at 5%.

Latent Variable	**Path Coefficient**	**T-Statistic (α =0.1)**	**T-Statistic (α =0.05)**
MP - > CCA	0.211	1.451	1.344
CP - > CCA	0.168	1.655*	1.156
NP - > CCA	0.260	2.144*	2.326**

Table 6: Path Coefficients and their Significance at Sig=10% (*) and Sig=5% (**)

The effect size of each path from an exogenous variable to an endogenous variable was evaluated using Cohen's f^2. The effect size is calculated as the increase in R^2 of the latent variable to which the path is connected, relative to the latent variable's proportion of unexplained variance (Chin, 1998). Cohen's f^2 was estimated by means of bootstrapping. According to Gefen et al. (2011), f^2 values of between 0.020 and 0.150, between 0.150 and 0.350, and exceeding 0.350 indicate that an exogenous latent variable has a small, medium, or large effect on an endogenous latent variable. The formula (f^2)=R^2 (included)-R^2(excluded)/(1-R^2(included)) was used to calculate the effect size, the results of which are presented in Table 6. All the latent variables had a small effect size.

The last structural model validity criterion that was evaluated was the predictive relevance of the exogenous latent variables on the endogenous latent variables. This criterion was evaluated using the Stone-Geisser's Q^2 test. This test uses a blindfolding procedure to create estimates of residual variances (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). Given that the total number of observations in the study was 93 (n=93), the omission distance in the blindfolding setup was set to 7 following the recommendation of Hair et al. (2014, p. 167) that the omission distance should be between 5 and 7 and that the number of total observations used in the model estimation divided by the omission distance (d) is not an integer (n mod d=0). The Q^2 values of all the latent variables MP, CP, NP, and CCA were above the 0 (Q^2 >0) threshold suggested by Fornell and Cha (as cited in Urbach and Uhlemann, 2010).

Latent Constructs	CCA	
	f^2	q2
MP	0.026	0.354
CP	0.063	0.142
NP	0.082	0. 127

Table 7: f2 and q2 Values of Latent Constructs

Hypothesis Testing

Following the evaluation of the reliability and validity of both the measurement and the structural models, a test of hypotheses was conducted in order to achieve the study's objectives. The hypotheses were formulated based on relevant theories and previous empirical studies. In order to test the hypotheses, partial least squares SEM as implemented in SmartPLS 3.2.1 were used. A summary of the results of the path coefficients, T statistics, level of significance, and effect sizes are presented in Table 5 and Table 6.

The first hypothesis of the study was that a relationship between mimetic pressures and cloud computing adoption exists. The hypothesis was formulated based on relevant theories and extant empirical studies. The latent variable mimetic pressures was specified in terms of four formative indicators. The measures for path coefficient were β=0.168, t=1.344(significant level=5%), f2=0.026, and q2=0.354. The relationship was found not to be significant ($t < 1.96$). The hypothesis that there is a relationship between mimetic pressures and cloud computing adoption was not supported.

The second hypothesis was that there exists a relationship between coercive forces and cloud computing adoption. The latent variable coercive pressures were specified in terms of four formative indicators. The measures for path coefficient was β=0.211, t=1.655(significance level=10%), f2=0.063, and q2=0.142. The relationship between coercive forces and cloud computing adoption was found to be significant ($t > 1.65$). The hypothesis that there exists a relationship between coercive pressures and cloud computing adoption was supported.

The last hypothesis was that there exists a relationship between normative pressures and cloud computing adoption. The latent variable normative pressures were specified in terms of four formative indicators. The measures for path coefficient were β=0.260, t=2.326 (significance level=5%), f2=0.082, and q2=0.127. The relationship between normative forces and cloud computing adoption was found to be significant ($t > 1.96$). The hypothesis that there exists a relationship between normative pressures and cloud computing adoption was supported. The path coefficients, indicator loadings, and the R^2 are summarized in Figure 2.

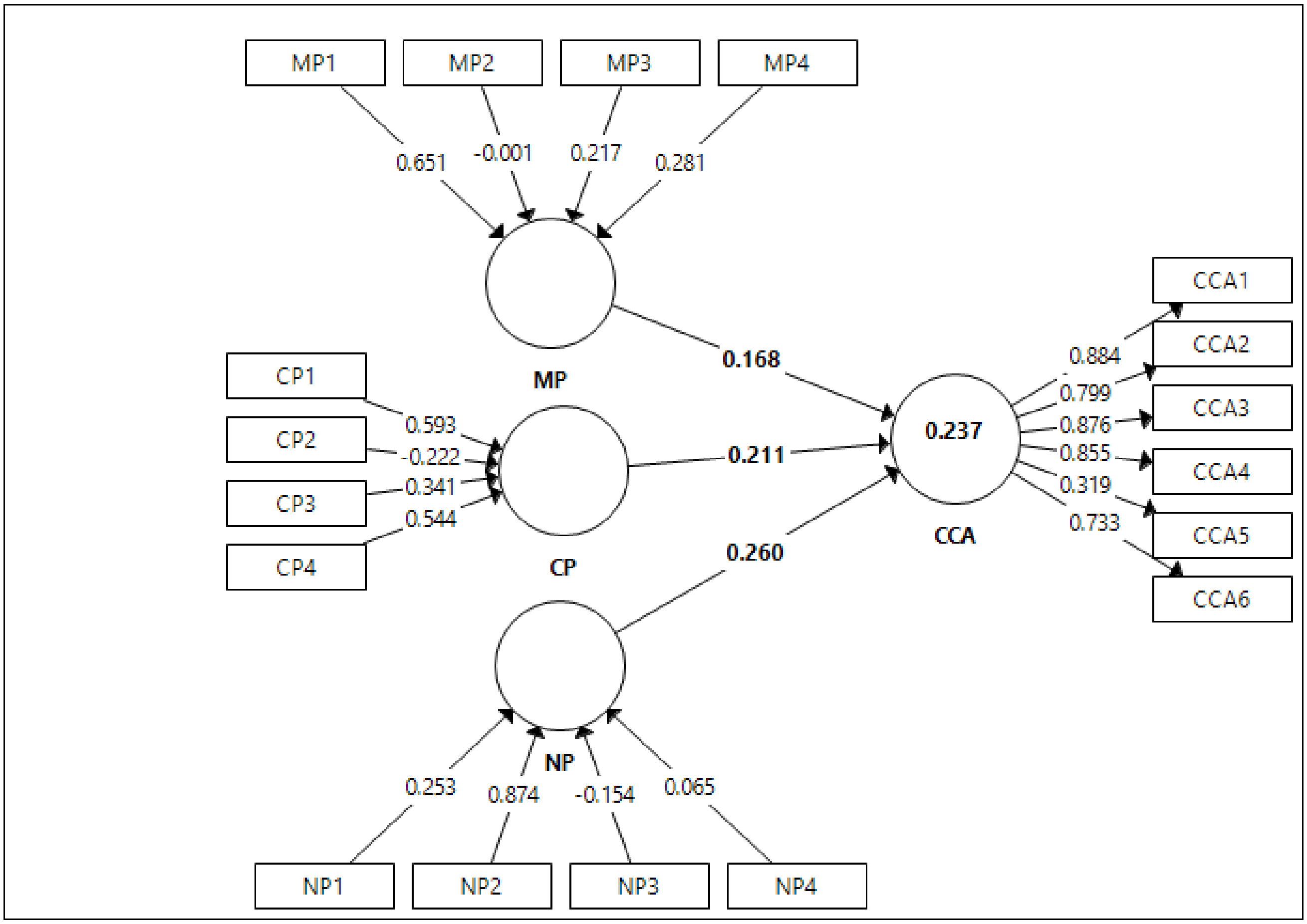

Figure 2: Path coefficients, indicator loadings and R^2

DISCUSSION

The first point of discussion regards the reliability and validity of the proposed framework. In general, the proposed framework (Figure 1) meets an adequate level of statistical fit. The model predictive relevance for all the latent variables estimated through the Stone-Geisser's Q^2 test yielded a result of q2>0 as recommended (Table 7). This indicates that in general, the conceptual framework employed reveals itself to be coherent when applied to selected firms in Kenya. The R^2 for the structural model was 0.237 indicating a weak explanatory power (Figure 2). The conceptual framework was based on the institutional theory and its role in cloud computing adoption. Under institutional pressures, organizations will implement strategies in order to gain, maintain, or repair their legitimacy (Suchman, 1995). The central underlying assumption of the institutional theory is that organizations and organizational actors seek to gain legitimacy in their environments in order to be accepted and thus ensure their long term survival (Meyer & Rowan, 1977). The results of a literature review conducted by El-Gazzar and Wahid (2013) on various empirical studies on cloud computing showed that the various institutional actors: cloud computing vendors, peer organizations, business partners, professional and business associations, and industry regulators played influential roles in cloud computing adoption. Recently, a study conducted to investigate the role of institutional forces on top management also confirmed that the institutional pressures influenced managers' beliefs concerning cloud computing solutions (Yigitbasioglu, 2015).

The first hypothesis that mimetic pressures have a relationship with cloud computing adoption was not supported. Mimetic pressures manifest themselves in the prevalence of a practice in the focal organization's industry and the perceived success of organizations within the focal organization's industry that have adopted a practice (Haveman, 1993 as cited in Teo et al. 2003). A study by Trope (2014) concluded that greater mimetic pressures led to greater adoption of cloud computing. The fact that the role of mimetic pressures in cloud computing adoption was not supported within the Kenyan context can be attributed to inadequate media coverage of cloud computing adoption initiatives by reputable organizations locally. According to Hu et al. (1997), media coverage of IT innovation adoption serves to strengthen the effects of mimetic pressures. Such publicized examples may also drive the adoption strategy of organizations in terms of what vendors to choose and the type of applications to be outsourced by drawing from the common pool of competence (Swanson & Ramiller, 2004).

The second hypothesis that there is a relationship between coercive pressures and cloud computing adoption was supported. Coercive pressures are defined as formal or informal pressures exerted on an organization by other organizations upon which they are dependent (DiMaggio & Powell, 1983). This study confirms the results of previous studies (Teo et al., 2003; Yigitbasioglu, 2015) that coercive pressures influence cloud computing adoption by organizations. On the other hand, some studies have indicated that firms do not succumb to coercive pressures when making cloud computing adoption decisions (Kung, Cegielski, & Kung, 2015; Trope, 2014). This variation in results regarding the role of coercive pressures in cloud computing adoption can be attributed to the different contexts in which the studies were conducted. Studies show that one of the challenges of cloud computing adoption is regulatory ambiguity in most countries (Ernst & Young, 2011; Kim, 2009; KPMG, 2011). Extant literature has noted that a lack of government regulations can hinder enterprises from adopting the cloud

(Lian et al., 2014; Luoma & Nyberg, 2011; Nkhoma & Dang, 2013). An implication of this is that understanding of the nature of the environment within which the firms operate and how that affects their interest in adopting cloud computing may be crucial in cloud computing marketing efforts..

The third hypothesis that normative pressures have a relationship with cloud computing adoption was supported. Normative pressures manifest themselves through inter-organizational channels of firm-supplier and firm-customer, as well as through professional, trade, business, and other key organizations (DiMaggio & Powell, 1983). Through normative pressures, organizations are expected to conform to standards of professionalism and to adopt systems and techniques considered to be best practices by relevant professional bodies (Kung et al., 2015). When normative pressures are high, organizations adopt innovations not on account of their assessments of the innovation's potential efficiency but on account of bandwagon pressure caused by the sheer number of firms that have already adopted that innovation (Abrahamson & Rosenkopf, 1993). The findings of this study support that of Basaglia et al. (2008), who found out that the main source of normative pressures is from suppliers and customers. Recently, in a study on adoption of software as a service (SaaS), one of the cloud computing service models concluded that normative pressures have a significant positive effect in the adoption of new technologies (Kung et al., 2015). However, a study by Trope (2014, p. 92) found from surveying firms in South Africa that the organizations' suppliers or the professional bodies they subscribe to did not influence their cloud computing adoption decisions. The mixed results signal the fact that cloud computing discourse through professional bodies and industry associations may be minimal and lacks clarity. In a study about open source adoption, Marsan and Pare (2013) concluded that lack of clarity, consistency, and richness of discourse hinders the adoption of an IT innovation.

CONCLUSION

The objectives of the study were achieved by testing the hypotheses captured in the study's research model. We used the PLS-SEM flavour of structural equation modelling (SEM) to evaluate the research model and test the hypotheses. The first hypothesis that states that there is a relationship between mimetic forces and cloud computing adoption was not supported. The hypothesis that states that there is a relationship between coercive pressures and cloud computing adoption was supported. The last hypothesis that states that there is a relationship between normative forces and cloud computing adoption was also supported. The study confirms that institutional theory is still relevant for understanding and explaining IT innovation adoption by business enterprises. Most of the studies that have employed institutional theory to understand IT innovation have done so within the context of developed countries. The results of this study imply that the theory's utility extends even to organizations in the developing countries.

The findings of this study should be interpreted and generalized in the light of a number of limitations. Since the study was conducted in Kenya and the sample selected from the financial, ICT, and manufacturing firms, the generalizability of the results may be limited to Kenyan organizations and those firms in similar institutional contexts. The approach of sampling firms from different sectors instead of a single sector was adopted due to the fact that cloud computing adoption is still at the early stages in Kenya, making it difficult to collect adequate data from a single sector or industry. The study used self-reported data from managers with ICT-related responsibilities, which may have resulted in either acquiescent responding or reactant responding (Paulhus & Vazire, 2007).

In order to better understand constructs like institutional pressures and cloud computing adoption as processes that change over time, further research should explore the use of longitudinal surveys to study various IT innovation determinants and antecedents. As longitudinal surveys are not the panacea to measurement challenges in IS research, the longitudinal survey represents a logical extension of the cross-sectional study and provides a useful approach for studying change and adaptation in IS domains (Venkatesh & Vitalari, 1991). Further, not all cloud service providers own and operate data centres. Many of them are intermediary service providers or, more specifically, cloud service brokers. Further studies should explore the role played by cloud brokerage service companies and the value they add to the cloud value chain.

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