



Beyond Data Analytics and Hybrid Wireless Networks in Cloud Services-Oriented Enterprises

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ABSTRACT

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With rapid digital transformation, it is becoming critical to apply emerging technologies in improving the management of organizational data and competitiveness by integrating artificial intelligence (AI), Internet of things (IoT), cloud computing, and 5G networks. This paper presents the impact of adoption of AI-based analytics, internet of things in hybrid networks, cloud computing and 5G technology on Data Integration Quality and Security (DIQS) and subsequent effect on Enterprise Capabilities (EC) in cloud services-based businesses. The empirical results of PLS-SEM, based survey data of 410 managers, indicate that technological adoption makes a significant contribution to DIQS, which subsequently leads to efficiency, scalability, and security of the enterprise. Moreover, organizational size (OS) does moderate the DIQS-EC relationship, which implies that the larger firms have greater general profit in using data integration strategies to enhance the quality of information. The research is an addition to the literature on digital transformation by providing a multidimensional parameter, which connects technology adoption with development of enterprise capacity. Organizations that seek to make use of the emerging technologies to enhance data governance and operational excellence are given practical implications. Future studies are to focus on the formulation of how regulatory frameworks and cybersecurity policies continue to influence the building of enterprise capability.



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1. Introduction

Over the past few decades, the cloud computing technologies have been actively used by companies of different industries to achieve a greater degree of flexibility, scalability, and cost-effectiveness (Gangwar et al., 2015; Oliveira et al., 2014). Enterprises that are cloud services based are gaining strength and this represents a paradigm shift in business operations, i.e. physical resources to digital infrastructure. What is more important is that the value of the additional technologies such as AI-driven analytics and the IoT-powered hybrid wireless networks have become a force to reckon with, altering the enterprise strategy (Lee & Lee, 2015; Popović et al., 2018). It is not a gradual change of how companies operate, the management of data and securing their information but a reconsideration of all business dimensions (Bharadwaj et al., 2013; Wamba et al., 2017).

The AI-based analytics of new capabilities exceeds the capability of the traditional data analysis techniques that enable enterprises to utilize the actionable insights to execute decisions, enhance processes and establish resource allocation (Wamba et al., 2017). These analytics solutions allow companies to harness advanced algorithms to obtain real-time intelligence besides predictive intelligence over large volumes of data in order to radically transform novel enterprise potentials in relation to effectiveness, scalability and safety (Bharadwaj et al., 2013; Ransbotham & Kiron, 2017). The use of predictive analytics is becoming more popular among organizations nowadays to predict upcoming market changes and client behavior to make proactive strategic decisions and correct operations (Popovič et al., 2018).

Similarly, IoT of hybrid wireless network is another important innovation since it offers smooth connection in terms of devices, sensors and digital systems. Enterprises can be monitored in real-time with the help of IoT technologies, and it enhances the transparency and agility in operations in response to the market changes (Hsu & Lin, 2016; Lee & Lee, 2015). The strong and sound data collection solutions offered by IoT technologies on numerous touch points in the enterprise increase the quality of collected data to be used in analytics (Gorla et al., 2010). The integration of IoT and hybrid wireless networks allows providing highly interconnected and flexible infrastructure that takes advantage of the rapid technological and market evolution (Lee & Lee, 2015).

All of these have been proceeding in tandem with the usage of cloud computing and 5G technologies which are also continuing to drive the same. Garrison et al. (2015) and Gangwar et al. (2015) define cloud computing as a system where enterprises are provided with infrastructure as a foundation of scalable storage and analytics systems and rapid implementation of innovative solutions. The result of this transition is reduced initial capital spending, ease of collaboration of the supply chain, and enormous flexibility in its operations, as the supply chain can be scaled up or down very fast, which is affected by the fluctuations in demand (Oliveira et al., 2014). Moreover, the use of the 5G technology is associated with a lower total data transfer speed, low latency and increased reliability, which may be crucial to the support of the IoT driven applications and real-time analytics (Chih-Lin et al., 2016; Kshetri & Voas, 2020).

However, the potential payoff of using these advanced technologies is not received by all enterprises in the same manner due to vastly different enterprises' capability to integrate and take advantage of these advancements. There are variations in organizational size and technology of technology infrastructure (Teo & Pian, 2004; Yadegaridehkordi et al., 2018) that significantly influence the effective use of data analytics and IoT technologies. Big organizations have more resources to hand as well as established processes which means they can reap more benefits from disconnected integrations of advanced technology than small enterprises (Benlian & Hess, 2011; Yadegaridehkordi et al., 2018). On the other hand, smaller enterprises may encounter difficulties in utilizing advanced technological solutions like the lack of budget, insufficiency of technical expertise, and insufficient existing infrastructure to enable it to have optimum utilization (Teo & Pian, 2004).

In addition, due to the growing dependence of enterprises on cloud services, cloud data integration quality as well as security has become crucial. An effective data integration delivers chlorinated data seamlessly between various platforms and databases by maximizing the value of data analytics and IoT technologies (Gorla et al., 2010; Ransbotham & Kiron, 2017). Same as security concerns have also increased because cloud-based data is sensitive and hybrid wireless networks have complexities. Cybersecurity incidents and data breaches have been high profile and have been a strong reason for robust security mechanisms at an enterprise level leading to an overall capability for efficiency, scalability and security (Bharadwaj et al., 2013; Kshetri & Voas, 2020).

In the competitive market of the global business, enterprises are challenged to maintain the continual improvement of efficiency, responsiveness, and innovation. Advanced technologies like AI-enabled analytics, IoT-enabled networks, Cloud computing adoption and emerging 5G technology create large opportunities for enterprises to secure their sustainable competitive advantage (Garrison et al., 2015; Wamba et al., 2017). A

knowledge of these complex dynamics is needed to adequately make strategic decisions and gain improved performance outcomes.

To fill this knowledge gap, this research focuses on how advanced technological integrations affect the enterprise capabilities by data integration quality and security moderated by the organizational size. The insights resulting from findings will be useful for guiding entrepreneurs towards using advanced technology to help them to become more competitive, and more sustainable.

2. Literature Review

The studies that are relevant to each hypothesis of how advanced technological integration impacts cloud services-oriented Enterprises are reviewed systematically in this section. Every sub-section covers a review of previous studies to comprehend how technologies such as Cloud Computing, AI-driven Analytics, the Internet of Things and 5G adoption affect Data Integration Quality and security (DIQS) and consequently impact Enterprise Capabilities (EC). The direct impact and moderating part of Organizational Size (OS) in the literature is also investigated. Every sub-section ends with a well-defined hypothesis that will enable a good empirical examination. This section ends with the presentation of the conceptual framework.

2.1. Adoption of Cloud Computing and DIQS

Cloud computing brings about great improvements in data management of an enterprise by maintaining consistency, reliability and security across platforms. According to prior studies, cloud computing enables integration processes making use of effective standardization and management of data (Al-Ruithe et al., 2018; Marston et al., 2011). Sultan (2014) believes that the adoption of the cloud fosters better data governance practices and hence higher the organization's security levels. Lian et al. (2014) also indicate that Enterprises that use cloud computing acquire significant dividends concerning data quality and operational efficiency. Low et al. (2011) and Morgan and Conboy (2013) provide empirical evidence that cloud computing is of high importance for large improvement of enterprise responsiveness and integration quality. Secondly, technological readiness, and management support, among other factors are identified by Bhattacharjee and Park (2014) and Park and Kim (2014), as well as Senyo et al. (2016) as key success factors in cloud implementation. Therefore:

H1: The adoption of cloud computing has a positive impact on the quality and security of data integration (DIQS) in cloud services-oriented enterprises.

2.2. AI-driven Analytics and DIQS

AI-driven analytics enormously improves the handling of enterprise data through improved accuracy, consistency and decision-making. In their work from Davenport and Ronanki (2018) show that with AI analytics data relevance and integration, quality is greatly enabled, and businesses can achieve true strategic insights. Continuing, Duan et al. (2019) also, specify how AI-based analytics platforms notably increase data governance and organizational security. As stated by Brynjolfsson and McAfee (2017), Elgendy and Elragal (2014) analytics powered by AI and its capabilities are essential to enable data to be processed more efficiently and with more accuracy. Moreover, Analytics (2018) and Wixom and Watson (2010), among others, mention the strategic benefit supported by robust AI analytics and enhanced data integration quality. Hence:

H2: The AI powered Analytics has a positive effect on Data Integration Quality and Security (DIQS) in Cloud Services oriented corporations.

2.3. Adoption of 5G Technology and DIQS

The adoption of 5G technology makes a massive difference to an enterprise to improve data capabilities by providing better network efficiency, reduced latency and better integration processes. 5G significantly improves data transmission and integration quality and it provides reliable connectivity across diverse enterprise environments which is

supported by Andrews et al. (2014), and Gupta and Jha (2015). According to studies involving Akpakwu et al. (2018) and Wang et al. (2019), 5G is proven to have other security advantages through strengthened encryption and comprehensive security architecture. As elucidated by He et al. (2022) and Taleb et al. (2017) each enterprise that utilizes 5G benefits from greater data handling security and operational agility. Lema et al. (2017) and Agiwal et al. (2016) also confirm that the 5G advanced network capabilities directly impact better organizational data governance and integration quality. Hence:

H3: The proposed H2 is that the adoption of 5G technology positively impacts Data Integration Quality and Security (DIQS) in cloud services-oriented enterprises.

2.4. IoT in Hybrid Networks and DIQS

Integrating IoT into hybrid networks greatly improves data integration, which leads to greater security. Atzori et al. (2010) and Whitmore et al. (2015) noted the capabilities of IoT deployment in collecting and integrating data in multiple platforms that enhance accuracy and security. Madakam et al. (2015) mention the role of IoT in achieving real-time data synchronization and improving organizational transparency. As stated by Stankovic (2014) and Da Xu et al. (2014) the IoT technology offers continuous data monitoring mechanisms, which greatly enhances the data security of enterprises. Additionally, Lee and Lee (2015), Hossain and Muhammad (2016), as well as Wortmann and Flüchter (2015) studies, have disclosed that raising the use of hybrid IoT networks will significantly enhance enterprise data integration processes. Thus:

H4: IoT in Hybrid Networks has a positive influence on Data Integration Quality and Security (DIQS) in cloud services-oriented enterprises.

2.5. Mediation Role of DIQS

It is found that effective DIQS is an intervening variable mediating the relationship between technological advancement and EC enhancement. According to prior studies, data integration quality is an important mechanism that converts the adoption of new technologies into enhanced performance outcomes (Ghobakhloo et al., 2015; Mithas et al., 2011). Data integration allows an efficient exploitation of technological resources therefore providing the improvement of the scalability, security and efficiency of enterprise (Bharadwaj et al., 2013). Accordingly, Tallon et al. (2013) and Almajali et al. (2016) validate the pivotal mediating position of data integration and security in leveraging technological advances into firm valuable capabilities. Thus:

H5: Data Integration Quality and Security mediate the relationships between ACC, AIA, AT, HN, and Enterprise Capabilities (EC).

2.6. Organizational Size and Enterprise Capability (EC)

Enterprise capabilities depend largely on organizational size. A large enterprise often has more resources, a larger infrastructure, and already defined processes of operation, so it would give a greater chance to work with capabilities (Damanpour, 2010; Ettlie & Rubenstein, 1987). In addition, firms with a stronger ability to utilize technology due to their size can achieve better performance (Liang et al., 2007; Teo & Pian, 2004; Zhu et al., 2006). Therefore: EC is positively affected by Organizational Size (6).

2.7. Moderation by Organizational Size

This relationship between DIQS and EC is significantly moderated by organizational size. For large organizations which have ample resources and infrastructure, the improvements of DIQS can better bring the effects to enterprise (Hitt & Brynjolfsson, 1997; Teo & Pian, 2004; Zhu et al., 2006). Thus:

H7: The relationship between Data Integration Quality and Security (DIQS) and Enterprise Capabilities (EC) is moderated by Organizational Size such that it is stronger in larger organizations.

3. Methodology

3.1. Research Design and Approach

A quantitative research design is used in this study concerning how these technologies in the field of AI-driven analytics, IoT in hybrid networks, cloud computing adoption and 5G technology adoption affect Data Integration Quality and Security (DIQS) that ultimately impact Enterprise Capabilities (EC), in Cloud Services Oriented Enterprises (CSOEs). In addition, the study considers Organizational Size (OS) as the moderating variable. Partial Least Squares Structural Equation Modeling (PLS-SEM) is a robust statistical technique used to test the research framework and hypotheses with mediation and moderation effects (Leguina, 2015a).

3.2. Sample and Data Collection

A total of 410 respondents, consisting of managers and officials engaged in the CSOEs, were used in this study to collect the data. An enquiry was structured to bring out perceptions on AI analytics, IoT, cloud computing, 5G adoption, DIQS, EC, and OS. To ensure that the findings are generalizable the study used a random sampling technique based on diverse participation in different organizations.

3.3. Measurement of Constructs

The measures used for each construct in this study were adapted from previous research and validated multi-item scales as used in the construct literature demonstrating reliability and validity (Hair Jr et al., 2023). Table 1 shows the number of items, sources and the measurement scale for each of the constructs presented.

3.4. Data Analysis Method

Being capable of handling the complex relationships such as mediating, moderating and direct effects in a variances-based SEM framework, PLS-SEM was chosen to be the principal statistical approach (Leguina, 2015a). Based on a two-stage approach, the analysis was performed using SmartPLS 4.0. In the first stage, measurement model evaluation was conducted to assess convergent validity, discriminant validity and reliability, with the constructs being tested against the required statistical criteria. To confirm the consistency and validity of the constructs, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were used to evaluate them (Hair Jr et al., 2023).

The second stage of the work consisted of the testing of the formulated hypotheses presented by the structural model evaluation. In this, path coefficients, t-statistics and p-values were used to determine the significance of the relationship between variables (Sarstedt et al., 2017). The Mediating and Moderating effects of the proposed interactions were also checked to verify their impact on cloud services-oriented enterprises and the proposed interactions.

3.5. Ethical Considerations

This study employed ethical research guidelines to ensure confidentiality, consent, and voluntary participation. However, participants selected to participate in the study at their own risk and were informed about the purpose of the study, and the responses received were anonymous. Data collection was ensured to be compliant with research ethics and has been seeking ethical approval as well.

4. Results

This section demonstrates findings from Partial Least Squares Structural Equation Modeling (PLS SEM) for the evaluations of AI-driven analytics, IoT in hybrid networks, cloud computing adoption, and 5G technology adoption for Data Integration Quality and Security (DIQS) and the influence of DIQS in the enterprise capabilities (EC). In the first step, the construct validity, reliability and discriminant validity are examined using Cronbach's alpha,

composite reliability, and average variance extracted (AVE) in the measurement model evaluation. Next, structural model evaluation is done where the hypotheses are tested with path coefficients, t statistics and significant values to assess the impact of relationships. Results are discussed about how technology adoption facilitates data integration and enterprise capabilities and about the moderating effect of Organizational Size (OS). The assessment of the measurement and structural models is elaborated in the following subsections.

Table 1
Convergent Validity Test

Constructs	items	Loading	Alpha	CR	AVE
ACC	ACC1	0.842	0.906	0.93	0.727
	ACC2	0.874			
	ACC3	0.819			
	ACC4	0.833			
	ACC5	0.894			
AIA	AIA1	0.822	0.878	0.911	0.671
	AIA2	0.830			
	AIA3	0.816			
	AIA4	0.844			
	AIA5	0.782			
AT	AT1	0.831	0.826	0.884	0.656
	AT2	0.796			
	AT3	0.798			
	AT4	0.814			
DIQS	DIQS1	0.789	0.881	0.91	0.627
	DIQS2	0.816			
	DIQS3	0.833			
	DIQS4	0.780			
	DIQS5	0.769			
	DIQS6	0.759			
EC	EC1	0.765	0.871	0.903	0.608
	EC2	0.778			
	EC3	0.779			
	EC4	0.782			
	EC5	0.791			
	EC6	0.781			
HN	HN1	0.879	0.92	0.94	0.759
	HN2	0.87			
	HN3	0.87			
	HN4	0.861			
	HN5	0.874			
OS	OS1	0.845	0.818	0.891	0.732
	OS2	0.842			
	OS3	0.879			

The convergent validity test results of all the constructs for the internal consistency, reliability, and validity of the measurement model are presented in Table 1. Convergent validity implies a strong correlation among the items that measure the same construct (Leguina, 2015b). It can be seen that all constructs have factor loadings Fornell and Larcker (1981) which are more than the recommended thresholds (>0.70), Cronbach's alpha (≥ 0.70), Composite reliability ($CR \geq 0.70$), and Average variance extracted ($AVE \geq 0.50$).

Item reliability is supported by all individual item loadings of 0.75 and above. Cronbach's Alpha value ranges from 0.818 (OS) to 0.920 (HN), which reflects excellent internal consistency given the high number of questions found in the questionnaires used. In addition, the CR values from 0.884 to 0.940 provide further support for the reliability of the constructs. AVE values are higher than 0.50, the lowest (EC) equals 0.608 and the highest (HN) at 0.759, meaning latent constructs do a good job in explaining variance.

This adds support to that the measurement model has very strong internal consistency, reliability, and convergent validity, which would imply that the constructs are represented by their items. It has to be validated before structural model evaluation and hypothesis testing are performed (Sarstedt et al., 2017).

Table 2

HTMT Ratio

	ACC	AIA	AT	DIQS	EC	HN	OS
ACC							
AIA	0.056						
AT	0.043	0.053					
DIQS	0.384	0.315	0.389				
EC	0.197	0.096	0.119	0.452			
HN	0.047	0.094	0.081	0.332	0.155		
OS	0.038	0.093	0.077	0.149	0.413	0.066	

The Heterotrait-Monotrait (HTMT) ratio results shown in Table 2 assess discriminant validity, such that constructs are distinct from one another (Henseler et al., 2015). All construct pairs have HTMT values well below the recommended threshold of 0.85 that suggest strong discriminant validity (Leguina, 2015b). The highest HTMT value, 0.452 (DIQS → EC), confirms that the constructs are not correlated. Due to all these values satisfying the needed criteria, all the results confirm that the model constructs are statistically different and, therefore, the structural model evaluation is reliable.

Table 3
Fornell Larcker

	ACC	AIA	AT	DIQS	EC	HN	OS
ACC	0.853						
AIA	0.019	0.819					
AT	-0.02	-0.015	0.81				
DIQS	0.346	0.278	0.334	0.792			
EC	0.173	0.072	0.077	0.398	0.779		
HN	0.024	-0.081	-0.052	0.301	0.14	0.871	
OS	0.016	0.069	0.047	0.125	0.353	0.049	0.856

The Fornell-Larcker criterion represented in Table 3 serves as a common methodology to validate discriminant validity within structural equation modeling, according to Fornell and Larcker (1981). The square root of AVE (the diagonal elements) needs to be greater than any off-diagonal correlation values between constructs. This table validates the adequate discriminant validity of constructs because its diagonal values surpass all off-diagonal values according to Fornell and Larcker (1981).

The square root of AVE for Data Integration Quality and Security (DIQS) reaches 0.792, thus surpassing its correlations with both AI-driven Analytics (AIA) at 0.278 and Enterprise Capabilities (EC) at 0.398. The empirical separation between all measured constructs appears consistently throughout the analysis results. The measured concepts demonstrate unique characteristics through these testing results which uphold the validity of the structural model.

Table 4
Cross Loadings

	ACC	AIA	AT	DIQS	EC	HN	OS
ACC1	0.842	-0.032	-0.007	0.324	0.141	0.064	0.039
ACC2	0.874	0.034	0.026	0.321	0.165	-0.023	0.014
ACC3	0.819	0.04	-0.048	0.276	0.142	-0.001	-0.014
ACC4	0.833	0.045	-0.032	0.252	0.167	0.033	-0.021
ACC5	0.894	0.005	-0.032	0.291	0.124	0.031	0.04
AIA1	0.013	0.822	-0.03	0.238	0.077	-0.052	0.092
AIA2	0.07	0.83	0.029	0.243	0.057	-0.11	0.023
AIA3	-0.01	0.816	-0.019	0.228	0.017	-0.024	-0.005
AIA4	0.024	0.844	-0.05	0.227	0.059	-0.066	0.119
AIA5	-0.025	0.782	0.011	0.198	0.09	-0.078	0.052
AT1	-0.013	-0.021	0.831	0.276	0.112	-0.022	0.062
AT2	-0.006	-0.023	0.796	0.263	0.032	0.01	0.016
AT3	-0.014	0.013	0.798	0.297	0.076	-0.06	0.06
AT4	-0.031	-0.02	0.814	0.24	0.023	-0.099	0.006
DIQS1	0.255	0.229	0.269	0.789	0.295	0.229	0.045
DIQS2	0.282	0.227	0.296	0.816	0.329	0.244	0.141
DIQS3	0.308	0.257	0.281	0.833	0.31	0.234	0.09
DIQS4	0.264	0.182	0.242	0.78	0.36	0.304	0.089

DIQS5	0.245	0.206	0.272	0.769	0.308	0.226	0.09
DIQS6	0.288	0.217	0.223	0.759	0.284	0.186	0.139
EC1	0.198	0.115	0.109	0.348	0.765	0.13	0.18
EC2	0.101	0.022	0.06	0.275	0.778	0.134	0.308
EC3	0.115	0.084	0.102	0.382	0.779	0.095	0.254
EC4	0.152	0.099	0.087	0.263	0.782	0.051	0.286
EC5	0.15	0.021	-0.053	0.332	0.791	0.161	0.273
EC6	0.101	0.003	0.063	0.253	0.781	0.083	0.345
HN1	0.018	-0.087	-0.043	0.267	0.165	0.879	0.097
HN2	0.012	-0.068	-0.052	0.248	0.065	0.87	-0.01
HN3	0.047	-0.04	-0.063	0.283	0.13	0.87	0.032
HN4	0.012	-0.091	-0.063	0.248	0.145	0.861	0.061
HN5	0.014	-0.069	-0.004	0.26	0.104	0.874	0.031
OS1	0.018	0.066	0.04	0.12	0.288	0.04	0.845
OS2	0.014	0.02	0.091	0.079	0.269	0.016	0.842
OS3	0.01	0.083	0	0.118	0.342	0.064	0.879

Table 4 demonstrates how each construct item loads on its primary construct and other constructs for discriminant validity assessments in PLS-SEM (Hair et al., 2019). A proper indicator assessment requires its construct-specific loading to exceed all cross-loadings from other constructs, thus validating its measurement of the proper latent variable (Chin, 1998). All items demonstrate their highest value on their designated constructs according to the provided table, which verifies discriminant validity.

The relationship between ACC1 and the construct ACC demonstrates a loading value of 0.842, which exceeds the construct-loadings of ACC1 with other variables. The item measurements of AI-driven Analytics (AIA), Adoption of 5G (AT), Data Integration Quality and Security (DIQS), Enterprise Capabilities (EC), and IoT in Hybrid Networks (HN) alongside Organizational Size (OS) reflect the strong relationship with their respective constructs.

The measurement items adequately represent their specific constructs thus ensuring both reliability and validity of the model according to Fornell and Larcker (1981).

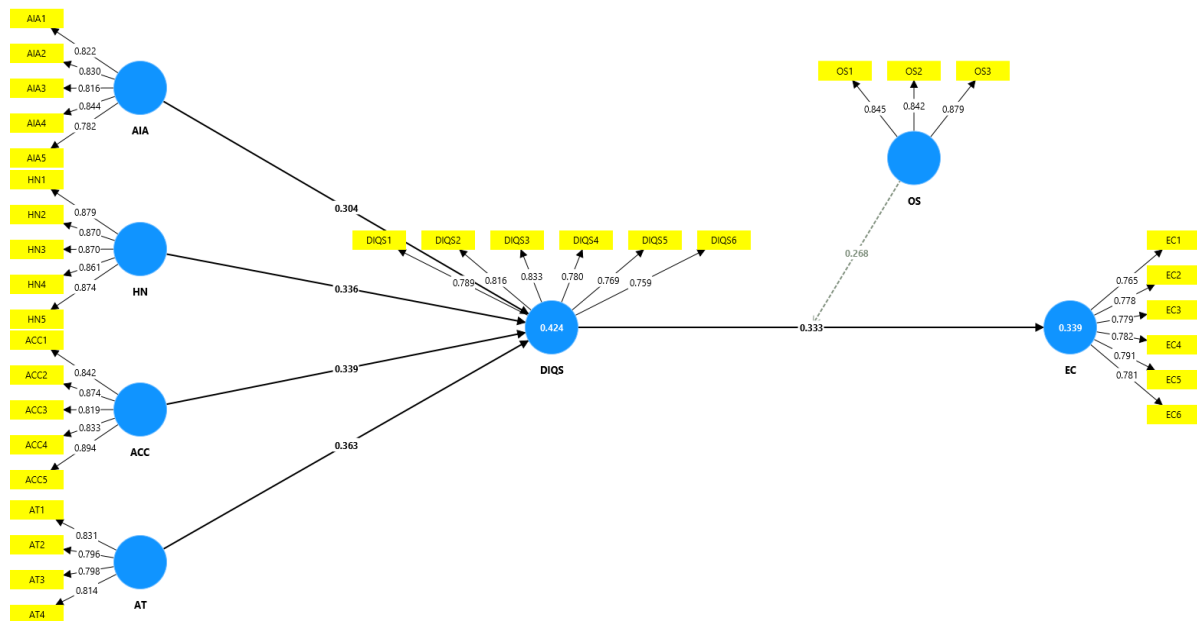


Figure 2: Measurement Model

The measurement model results are presented in Figure 2, showing the relationship that exists between observed variables (items) and their corresponding latent constructs. All outer loadings on the indicators (item reliability) are higher than the recommended threshold of 0.70 (Hair et al., 2019), which is an indication of strong indicator validity. With strong factor loadings, reliability is ensured for constructs such as AI-driven Analytics (AIA), IoT in Hybrid Networks (HN), Adoption of Cloud Computing (ACC), Adoption of 5G (AT), Data Integration Quality and Security (DIQS), Enterprise Capabilities (EC), and Organizational Size (OS).

The significant positive effects of relationships in the path coefficients (e.g., $AIA \rightarrow DIQS = 0.304$, $DIQS \rightarrow EC = 0.333$) are great. The role of OS is also found to be moderating (0.268). This finds confirmation in that the model has good reliability, validity and strong explanatory power for hypothesis testing (Sarstedt et al., 2017).

Table 5
Path Analysis

	Coef.	STDEV	t-stats	P values
ACC $\rightarrow$ DIQS	0.339	0.033	10.214	0.000
AIA $\rightarrow$ DIQS	0.304	0.038	8.024	0.000
AT $\rightarrow$ DIQS	0.363	0.036	10.156	0.000
HN $\rightarrow$ DIQS	0.336	0.039	8.668	0.000
DIQS $\rightarrow$ EC	0.333	0.044	7.644	0.000
OS $\rightarrow$ EC	0.326	0.044	7.431	0.000
OS x DIQS $\rightarrow$ EC	0.268	0.041	6.562	0.000

The path analysis results are presented in Table 5, which shows the strength and level of significance of the relationships in the structural model through Partial Least Squares Structural Equation Modeling (PLS-SEM). All direct paths have statistical significance ($p < 0.001$) which attest to good relationships among the constructs. The results indicate that the adoption of cloud computing ($ACC \rightarrow DIQS$, $\beta = 0.339$, $t = 10.214$), adoption of AI driven analytics ($AIA \rightarrow DIQS$, $\beta = 0.304$, $t = 8.024$), adoption of 5G technology ($AT \rightarrow DIQS$, $\beta = 0.363$, $t = 10.156$), and Internet of things in hybrid networks ($HN \rightarrow DIQS$, $\beta = 0.336$, $t = 8.668$) have a positive effect on Data Integration Quality and Security (DIQS), thus highlighting the importance of digital It is also indicated that DIQS also affects Enterprise Capabilities (EC) ($\beta = 0.333$, $t = 7.644$) which show the need for good synchronization of data in improving the organizational efficiency, scalability and security. Moreover, Organizational Size (OS) has a direct effect on EC ($\beta = 0.326$, $t = 7.431$), meaning that big firms experience a higher value from the introduction of digital technologies. The results suggest that OS has a moderating effect on $DIQS \rightarrow EC$ relationship ($\beta = 0.268$, $t = 6.562$), i.e. enterprises having higher resources can take better advantage of data integration. These findings verify the model, which is consistent with previous studies that stress the importance of the adoption of technology in improving the capabilities of the enterprise (Hair et al., 2019; Sarstedt et al., 2017).

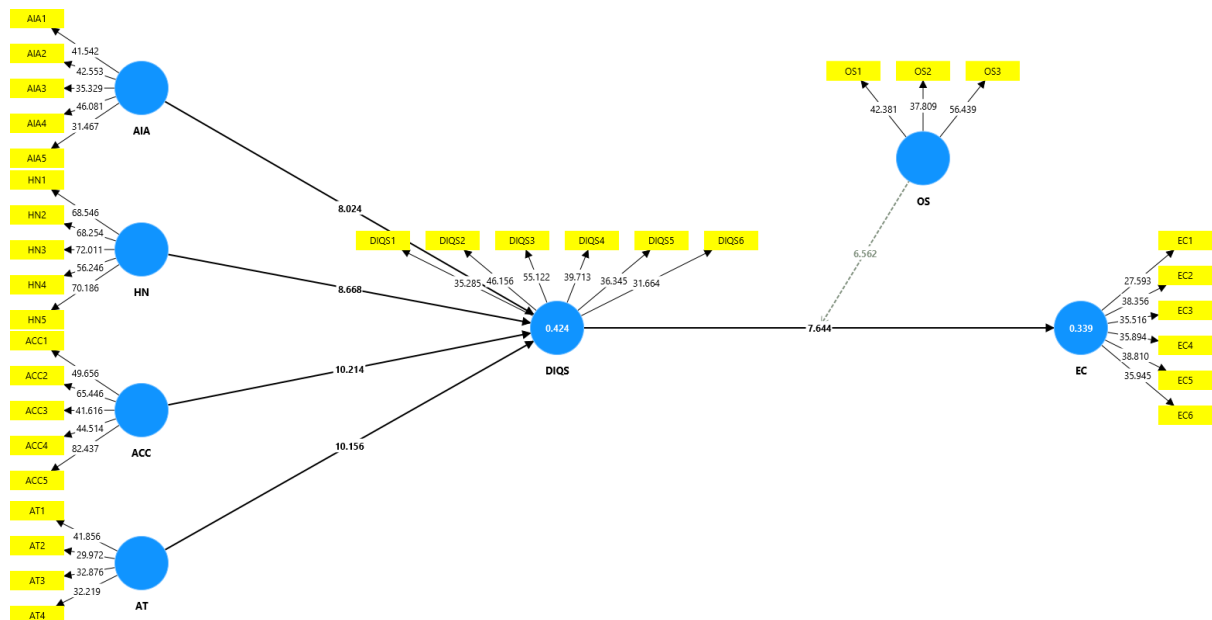


Figure 2: Structural Model

The structural model in Figure 2 depicts the relationships between constructs and all of the statistical significance in Partial Least Squares Structural Equation Modeling (PLS-SEM). The relationships are confirmed with standard t statistics and path coefficients that represent the strength. The strong impact of technology adoption on data integration quality and security (DIQS) is reflected on all the direct paths, i.e., $AIA \rightarrow DIQS$ ($t =$

8.024), $ACC \rightarrow DIQS$ ($t = 10.214$), $AT \rightarrow DIQS$ ($t = 10.156$), and $HN \rightarrow DIQS$ ($t = 8.668$). Moreover, DIQS is also found to significantly mediate the relationship between the Enterprise Capabilities (EC) ($t = 7.644$). Data integration improvements are further confirmed as influential in explaining factor differences (mean that are moderation by Organizational Size ($EC \rightarrow OS$) is statistically significant with $t = 6.562$). The hypothesized relationships, as well as the model robustness, are thus supported by these results (Hair et al., 2019; Sarstedt et al., 2017).

5. Discussion

This study finds the role of AI-driven analytics, IoT in hybrid networks, cloud computing adoption, 5G technology adoption in influencing Data Integration Quality and Security (DIQS) and consequent contribution to Enterprise Capabilities (EC) in cloud service-oriented enterprise. In addition, the study examined the moderateness of the Organizational Size (OS) on the association between DIQS and EC. This aligns with past literature and reaffirms the role of technological advancement in increasing data-driven enterprise efficiency, scalability, and security.

The study validates the assertion that the deployment of cloud computing, AI powered analytics, IoT on hybrid networking, and 5G technology plays a very positive role in DIQS, proving that DIQS links the best of digital technologies (Gangwar et al., 2015; Oliveira et al., 2014). The most influential of these technologies was 5G adoption ($\beta = 0.363$, $t = 10.156$), where high-speed connectivity, low latency, and strong encryption mechanisms contribute greatly to both data integration and security (Kshetri & Voas, 2020). This has also been proven in previous research that 5G networks enhance efficiency data handling and cloud-based enterprises cybersecurity (Agiwal et al., 2016).

Moreover, the value attributed to DIQS in $\beta = .304$, $t = 8.024$ indicates that AI is a key support in data governance, predictive analytics and anomaly detection to secure data (Davenport & Ronanki, 2018). Through AI-powered analytics, data is processed automatically, which results in higher accuracy and lowers the chances of a security breach (Duan et al., 2019). Researches from prior show that utilization of AI analytics improves operational efficiency in firms, such as extracting meaningful insights about complex datasets as well as optimizing data integration and security (Brynjolfsson & McAfee, 2017).

Furthermore, IoT in the hybrid networks ($HN \rightarrow DIQS$, $\beta = 0.336$, $t = 8.668$) was also found to enhance the data exchange and integration between the cloud-based enterprises. This is in line with Whitmore et al. (2015) and Lee and Lee (2015), since IoT networks driven by IoT facilitate real-time data synchronization and security, which help enterprises in minimizing the risk of data fragmentation. Realtime insights, along with continuous monitoring of enterprise networks, have been considered as the key driver of improved data security as perceived by IoT (Atzori et al., 2010).

The moderating effect of OS on the relationship between DIQS and EC was also studied ($\beta = 0.268$, $t = 6.562$). The results support the argument that organizational resources and infrastructure are crucial for realizing data-driven innovations, smaller enterprises seem to gain more from good data integration quality (Teo & Pian, 2004). Since large firms possess more advanced IT capabilities, they can better organize and conduct data integration processes, implement better security measures, and grow efficiently (Zhu et al., 2006).

There is support to this conclusion in prior studies, such that large firms have well-developed systems of data management, which facilitate how data are integrated and processed better than smaller firms (Hitt & Brynjolfsson, 1997; Liang et al., 2007). As such, DIQS is vital for any business, but the effect of DIQS on EC is more significant in large companies that can support technical desertion of complex data ecological systems more proficiently.

It is also indicative of the studies conducted by Ettlie and Rubenstein (1987) and Damanpour (2010) which argue that big companies can more easily adopt these technological advances since they are more able to optimize their enterprise functions using better data integration methods. Also, Tallon et al. (2013) support this statement as they

can indicate that larger companies incur greater costs on cybersecurity and compliance, which makes the association between DIQS and EC more noticeable.

Overall, the results discussion prove that technological adoption enhances DIQS and, consequently, Enterprise Capabilities (EC) in cloud services-based enterprises. Additionally, the relationship between DIQS and EC is moderated by the Organizational Size (OS) in that larger businesses gain more advantages because of introducing DIQS. Therefore, the results are consistent with the existing literature and underline the potential of cloud computing, analytics based on AI, IoT and 5G to enhance the performance of enterprises by enhancing the integration of data and the security of the latter. The insights have practical implications to companies that want to realize the maximum regarding their digital transformation approach and enhance their information management practices.

6. Conclusion, Implications, Limitations, and Future Research

Data Integration Quality and Security (DIQS), and its impact on Enterprise Capabilities (EC) in cloud services-based enterprises is assessed in this work in terms of the adoption of AI-driven analytics, the role of IoT in hybrid networks, cloud computing, and the role of 5G technology. The findings confirm DIQS is highly enhanced with the adaption of technology, among which are enhanced efficiency of the enterprise, scalability and security. In addition, the connection between DIQS and EC is mediated by Organizational Size (OS), which presupposes that bigger organizations have more to obtain with the same through embracing a more efficient data strategy of integration. The study confirms that digital transformation is a very important factor that can facilitate the optimal functioning and competitiveness of organizations in the cloud environment.

Theoretically, this research will add to the body of technology adoption and enterprise capability by demonstrating that advanced digital technologies help to integrate data and enterprise performance. OS is a moderate factor in emphasis of the fact that the size of firms influences the degree to which the firms gain on integration strategies. In a pragmatic sense, they provide resolute advice to the business leaders and IT strategists regarding strategic investment in cloud computing, AI-based analytics, 5G networks and IoT to ensure the security and integration of data. Big businesses should proceed and install modern data governance systems using their capital since the small businesses should consider more scalable strategies of digital transformation.

This research is, however, limited in some ways. The sample is reflective of cloud services-oriented businesses and hence cannot be extrapolated to other industries. Second, the data might be biased as it is reported. Longitudinal studies should be conducted in future to determine the effects of long-term implementation of technological innovations to the performance of the enterprise. Moreover, a closer examination of other possible moderating variables, including regulation policies, cybersecurity, and organizational culture, can provide a clearer picture of the way digital transformation enhances enterprise capabilities.

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