



Cloud Computing and Big Data Analytics in Smart City Information Systems

Ayomide Olugbade¹, Oluwaseun Abegunde², Moses Uyi Osagie³,
Chizube Obinna Chikezie⁴, Stephen Alaba John⁵, Anthony Ogechukwu Okolo⁶

¹ MSc Scholar, Department of Computing & Games, Teesside University, United Kingdom.
Email: ayomideolugbade34@gmail.com

² PhD Researcher, Computer Science and Engineering, University of Fairfax, United States.
Email: abegundeo@students.ufairfax.edu

³ Project Manager, Department of Information Technology, Xisco Technologies, United Kingdom.
Email: uyiosagie489@gmail.com

⁴ Data Scientist, School of Computing Engineering and Intelligent Systems, Ulster University, York Street, Belfast, United Kingdom. Email: kezie.c.o@gmail.com

⁵ Doctor of Finance, Department of Accounting and Finance, Kwara State University, Nigeria.
Email: stephenalaba.j@gmail.com

⁶ MSc Scholar, Master of Business, Terry College of Business, University of Georgia, United States.
Email: ogeokolo634@gmail.com

ARTICLE INFO

Article History:

Received: August 17, 2024
Revised: December 04, 2024
Accepted: December 18, 2024
Available Online: December 22, 2024

Keywords:

Smart City
Cloud Computing Infrastructure
Big Data Analytics
Organizational Support
Technological Readiness

ABSTRACT

This study aims to investigate how the Cloud Computing Infrastructure (CCI), Big Data Analytics Capabilities (BDAC), System Integration (SI), Information Quality (IQ), Organizational Support (OS), and Technological Readiness (TR) affect the effectiveness of Smart City Information System (SCISE) and how the mediating roles of SI and IQ as well as the moderating roles of OS and TR play in affecting SCISE. Data was collected from 500 professionals who are participants in smart city initiatives, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). It is found that SCISE can be significantly improved by both CCI and BDAC via improved SI and IQ. Finally, they further confirm the importance of organizational and technological context and emphasize OS and TR as these relationships. This study provides theoretical contributions and practical insights on how to further digital transformation in smart cities.



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Corresponding Author's Email: ayomideolugbade34@gmail.com

1. Introduction

Cities across the world are facing critical sustainability challenges and increasingly complex socio-economic issues as a result of the rapid growth of urban populations and the accelerating trend of urbanization (United Nations, 2019). Municipal administrations become overwhelmed with increasing demands to deliver efficient, sustainable, and inclusive service delivery as cities become denser, from traffic management, waste disposal, healthcare, public safety, environmental monitoring, and resource allocation to infrastructure optimization (Albino et al., 2015; Angelidou, 2015). To address these challenges, the smart cities concept has been proposed as a transformative paradigm to improve the quality of life, increase transparency in the city governance, and meet the goals of sustainable development of the environment (Yigitcanlar et al., 2018).

In essence, smart cities refer to the integration of smart ICT solutions into urban management to make cities more adaptive, sustainable, and responsive (Lee et al., 2014; Nam & Pardo, 2011). Information systems that process enormous amounts of data in real

time and help for better decision-making and operational effectiveness form an integral part of this transformation (Chatterjee et al., 2018). Cloud computing and big data analytics (BDA) as main technological enablers to build effective information systems of the smart city frameworks have been increasingly recognized as important for the smart cities infrastructure that is being built (Bibri, 2018; Hashem et al., 2016).

The concept of cloud computing, which includes scalable computing resources that are available over the internet, can guarantee several significant advantages to the organizations in terms of agility, cost efficiency, and responsiveness (Gangwar et al., 2015; Oliveira et al., 2014). Cloud-based technologies adopted by the municipalities lead to reduced cost of IT infrastructure, increased operational scalability, and efficient management of large volumes of citizen-centric services (Ali et al., 2016). It also helps cities to store, process, and analyze data from multiple and geographically scattered sources better and more securely, leading to better public service delivery (Yadav et al., 2018).

At the same time, big data analytics is a paradigm shift in the use of data, where cities have an opportunity to use large amounts of structured, semi-structured, and unstructured information (Akter et al., 2016; Gupta & George, 2016). The smart city planners may use advanced analytics to retrieve helpful information, determine trends, predict patterns, and make smart and evidence-based decisions to address urban challenges (Hashem et al., 2016; Kitchin, 2014). As an example, with the help of real time data analytics, the real-time monitoring, prediction and resource distribution in urban mobility, energy use, environmental sustainability can also be performed correctly (Bibri, 2018; Wang et al., 2015).

Although it is agreed that cloud computing and big data analytics can have a revolutionary potential, the integration and execution of these technologies in the context of smart city information systems is not that easy. The issues that occur are technological preparedness, data interoperability, the complications related to the system integration, quality of the data, security issues, and differences in support and commitment provided by the organizations (Khan et al., 2013; Oliveira et al., 2014). System integration (SI) is one of the most crucial aspects to support smart city solutions because smart city solutions imply the presence of heterogeneous technological platforms and data formats to be smoothly integrated to enable interactions between various departments, systems, and stakeholders (Garrison et al., 2015; Rai et al., 2006). The quality of information (IQ) is also a factor concerning the usability and effectiveness of smart city information systems in that the information quality available through such complex integrated systems is the accuracy, timeliness, completeness, and relevance of information (DeLone & McLean, 2003; Wixom & Todd, 2005).

Apart from technological and integration challenges, organizational support (OS) and technological readiness (TR) are critical for the success of smart city initiatives (Parasuraman, 2000; Premkumar & Roberts, 1999). Organizational support means the extent to which a city administration allocates required resources, funding, managerial commitment, and strategic emphasis on implementing new technologies (Wang & Wang, 2020). Technological readiness includes the technical skills, readiness of infrastructure, and the readiness of an organization to apply the innovative digital technologies for better performance (Alsaad et al., 2017; Lin & Hsieh, 2007). Organizational support and the technological readiness of cities help them use cloud computing and big data analytics to successfully implement and leverage them for achieving their desired operational effectiveness and citizen satisfaction (Angelidou, 2015; Chatterjee et al., 2018).

While, according to prior research, cloud computing and big data analytics are generally important in smart city contexts, empirical studies (viz., for the rigorous validation of mediation and moderation effects) that incorporate these constructs in a comprehensive theoretical model are relatively scarce (Bibri, 2018; Hashem et al., 2016). Therefore, the study is highly significant as it extends the existing literature by supplying empirically grounded insights into how the technological and organizational dimensions of a smart city information system jointly result in smart city information system effectiveness.

Additionally, the insights from this research can be used by city administrators, technology planners, and policymakers for decision-making, investment of technological infrastructure, and strategy development about organizational support and readiness enhancement from a practical point of view. Thus, identifying and addressing these dimensions will increase the potential success of the implementation of smart city significantly and bring higher benefits to urban residents and affect other broader socio-economic and environmental sustainability goals positively (Lee et al., 2014; Nam & Pardo, 2011).

Finally, there is no alternative to using smart city strategies to solve urban challenges and sustainability concerns. Cloud computing and big data analytics integrated with smart city information systems can provide a great opportunity for transformation in urban governance, for a targeted improvement of the quality of life of citizens, and to reach comprehensive sustainability. Hence, understanding the complex linkage between technological, organizational, and integration related factors is crucial; thus, the current study is relevant and important.

These objectives are attained in the remaining of the paper. The second section of the paper is a critical review of the literature concerning the critical theoretical underpinnings of cloud computing, big data analytics, system integration, and information quality and the unique combination of the constructs in the context of smart cities. Besides, the discussion of the methodological approach is described in detail, which includes sampling strategy, data collection methods, and methods of data analysis. It is then followed by the presentation of direct, mediation, and moderation analysis with clear results. Third, we speak about the theoretical and practical implications of these findings, contributions and limitations of the research and suggest other areas to research in the future.

2. Literature Review

This section examines the applicable scholarly literature, which addresses Cloud computing infrastructure (CCI) and Big Data analytics capabilities (BDAC), System integration (SI), Information quality (IQ), Organizational support (OS), Technological readiness (TR), and Smart city information system effectiveness (SCISE). The subsections conclude with hypotheses identified out of the literature review.

2.1. Cloud Computing Infrastructure (CCI)

Cloud computing Infrastructure involves the data processing properties that are provided by internet networks to process storage operations. The research studies underline the need to have cloud infrastructure deployed towards building scalable solutions to reduce costs and enhance management of data services within urban settings. Municipalities are enabled to effectively process large volumes of data on IoT sensors through cloud computing in addition to enhancing their real-time data analysis and city management capabilities (Aazam et al., 2014). The assimilation of the cloud technology will continue to be decisive due to the fact it offers scalable resource allocation functions and complex analytical tooling needed all over the smart cities (Botta et al., 2016; Stergiou et al., 2018). Cloud infrastructure provides necessary data storage services through available and protected data that the smart city management requires (Mehmood et al., 2017; Rathore et al., 2016). Studies indicate that cloud computing helps the city departments and stakeholders to collaborate, as Dastjerdi and Buyya (2016) and Santana et al. (2017). Cloud service platforms are the ones that can help minimize IT maintenance costs to generate enhanced budget management by municipalities (Baziana, 2024; Stępnia et al., 2021).

H1: Cloud Computing Infrastructure positively influences Information Quality.

H2: Cloud Computing Infrastructure positively influences System Integration.

H3: The relationship between Cloud Computing Infrastructure and Smart City Information System Effectiveness is mediated by Information Quality.

H4: The relationship between Cloud Computing Infrastructure and Smart City Information System Effectiveness is mediated by System Integration.

2.2. Big Data Analytics Capabilities (BDAC)

The Big Data Analytics Capabilities (BDAC) refer to methods incorporated with tools that can analyze large datasets to reveal significant information. Literature evidence demonstrates how BDAC processes unprocessed urban data to generate important information that smart cities need for their decisions (Hashem et al., 2016; Kitchin, 2014). BDAC allows analysts to conduct instant analyses of streaming information derived from sensors combined with social media data plus public database resources that support modern urban decision-making approaches (Ullah et al.). The improved analysis capabilities help maximize resources in transportation networks alongside waste management solutions and energy utility efficiency alongside public security requirements (Choi et al., 2017; Li et al., 2016). BDAC improves urban operational effectiveness through its ability to predict maintenance needs and service requirements, which helps authorities optimize resource deployment (Al Nuaimi et al., 2015; Batty, 2013; Duan & Xiong, 2015; Strohbach et al., 2015).

H5: Big Data Analytics Capabilities positively influence Information Quality.

H6: Big Data Analytics Capabilities positively influence System Integration.

H7: The relationship between Big Data Analytics Capabilities and Smart City Information System Effectiveness is mediated by Information Quality.

H8: The relationship between Big Data Analytics Capabilities and Smart City Information System Effectiveness is mediated by System Integration.

2.3. System Integration (SI)

Smart cities will need to integrate Systems to unite various technology systems with the city parts to work together. System Integration is the foundation of ensuring functionality in the interconnections of the integrated urban systems, such as transportation, utilities, and public safety, as proposed by Perera et al. (2014) and Jin et al. (2014). With the help of efficient integration, heterogeneous urban systems become integrated, which sets conditions of interoperability between the elements of the city and leads to an increase in the quality of services (Petrolo et al., 2017). The system integration leads to systematic data integration and, at the same time, allows organizations to control their activities with a single hand and attain greater and better results in their operations (Dameri & Cocchia, 2013; Schaffers et al., 2011). Integrative systems face performance restrictions due to the lack of interoperability rules and security concerns and challenges of linking old systems (Bélissent, 2010; Gil-Garcia et al., 2014; Theodoridis et al., 2013).

H9: System Integration positively influences Smart City Information System Effectiveness.

2.4. Information Quality (IQ)

Information Quality (IQ) is used to describe data qualities such as accuracy, reliability, completeness and timeliness, which are vital in making effective decisions. The level of smart cities directly results in improved decision outcomes and improved policies and more efficient resource allocation (Batini et al., 2009; Cai & Zhu, 2016). IQ leads to improved urban governance and citizen satisfaction in relation to the population, because literature in Neirotti et al. (2014) affirms that the implementation of IQ is related to improved urban governance and citizen contentment. The enhanced quality of information contributes to the high-performance tracking of the city and anticipatory management systems of the contemporary cities (Janssen et al., 2017). Wixom and Todd (2005) and Thomson (2011) and Wang and and Strong (1996) agree that the critical importance of IQ is specific to disaster management and healthcare delivery and sustainable urban planning.

H9: Information Quality positively influences Smart City Information System Effectiveness.

2.5. Organizational Support (OS)

Organizational Support (OS) is defined as a managerial commitment, sufficient resources and enabling environment to adopt technology. According to (1999) and

Tornatzky et al. (1990), Organizational Support has a significant impact on the successful implementation of smart city technologies as various literature studies indicate. They are crucial in overcoming the obstacles to adoption resistance and allocation of resources, and training needs of employees (Low et al., 2011; Oliveira et al., 2014) with the help of leadership that supports them and good management. Evidence of research indicates that organizations that offer certain means and aid attain quicker implementation and enhance technology working and facilitate easier adoption of innovation (Ifinedo, 2011; Wang & Wang, 2020). Organizational Structure (OS) is very favorable towards facilitating cultures of digital transformations that facilitate effective deployment within the smart urban setting (Henderson & Venkatraman, 1999; Weerakkody et al., 2011).

H10: Organizational Support positively influences Smart City Information System Effectiveness.

H11: Organizational Support moderates the relationship between Information Quality and Smart City Information System Effectiveness.

H12: Organizational Support moderates the relationship between System Integration and Smart City Information System Effectiveness.

2.6. Technological Readiness (TR)

An organization demonstrates Technological Readiness when it possesses suitable infrastructure together with skilled personnel to accept innovative approaches. TR serves as a critical factor in technology adoption success because organizations with greater readiness achieve better implementation results (Lin & Hsieh, 2007; Parasuraman, 2000). The literature demonstrates that cities with better technological readiness succeed more easily in implementing advanced Information and Communication Technology solutions for smart management (Shwedeh et al., 2022; Zhu et al., 2006). TR consists of well-trained personnel and suitable IT infrastructure with an environment welcoming to innovation (Alsaad et al., 2017; Ramayah et al., 2003). High technological readiness in organizations leads to improved efficiency during smart city project implementation, which results in better urban performance and satisfied citizens (Ajayan et al., 2020; Berardi, 2013; Danii, 2011; Shang & You, 2019).

H13: Technological Readiness positively influences Smart City Information System Effectiveness.

H14: Technological Readiness moderates the relationship between Information Quality and Smart City Information System Effectiveness.

H15: Technological Readiness moderates the relationship between System Integration and Smart City Information System Effectiveness.

2.7. Smart City Information System Effectiveness (SCISE)

The level which is described by SCISE is the level in which the smart city systems fulfill their purposes to improve the administration of cities as well as increasing the level of citizen satisfaction and reaching sustainability objectives. Different academic literature shows that properly adopted smart city systems attain overall positive effects such as improved services and operations efficiency, leading to urban resilience, as argued by Nam and Pardo (2011) and Lee et al. (2014). Anthopoulos (2015), Vanolo (2013), and Gil-Garcia et al. (2014) find smart city initiatives to be effective in the enhancement of transparency and people trust and proactive ruling. As the existing literature reflects, the effective measures of smart cities result in improved decision-making mechanisms and enhanced the work of the urban infrastructure as well as the creation of more community engagement, as discussed by Ruhlandt (2018) and Dameri and Cocchia (2013) and Dameri and Cocchia (2013).

3. Methodology

In this section, the methodology that is used in examining the effect of Cloud Computing Infrastructure (CCI) and Big Data Analytics Capabilities (BDAC) on Smart City Information System Effectiveness (SCISE) is identified with the mediator of System

Integration (SI) and Information Quality (IQ) and the moderator of Organizational Support (OS) and Technological Readiness (TR).

3.1. Research Design

The study employed quantitative research design to test the hypothesized relationships with the help of structural equation modeling. In this regard, the methodology is suitable to test the constructs of theory, which contains measured variables, and is useful in addressing the complex relationships between the variables of study, particularly in mediating and moderating the effects (Sarstedt et al., 2021).

3.2. Sampling and Data Collection

A questionnaire was distributed to 500 professionals who were actively engaged in smart city projects in various cities across the globe, that are, IT experts, urban planners as well as government officials. The participants were selected under purposive sampling to ensure the respondents possess the associated knowledge and experience regarding smart city activities. The approach is effective in a sense that it allows the researcher to target a given population of individuals that would be most likely to possess information and knowledge that can be used in the study (Etikan et al., 2016). The data was collected using a structured questionnaire that was administered online and in person and this enabled a broad and varied pool of respondents.

3.3. Instrumentation

The scales used to measure the study details were based on literature that was well known to ascertain the relevance and reliability of the constructs in the smart city project. They consisted of a structured questionnaire comprising constructs which were measured using five-point Likert scale, 1 (strongly disagree) to 5 (strongly agree). Oliveira et al. (2014) and Gangwar et al. (2015) came up with five items to use as the scale to determine the availability, accessibility, and reliability of cloud services of evaluated Cloud Computing Infrastructure (CCI). In the case of each of the six items that were picked regarding the big data analytics capabilities (BDAC) that were identified by Akter et al. (2016) and Gupta and George (2016), Four items were employed to gauge system integration (SI) as has been developed by Rai et al. (2006) and Garrison et al. (2015), in relation to the successful use of various digital systems and platforms in the smart city framework.

To evaluate the accuracy, timeliness, completeness and relevance of information produced by smart city systems, Information Quality (IQ) used the following five items proposed by DeLone and McLean (2003), Wixom and Todd (2005), and Gorla et al. (2010). To capture Organizational Support (OS), four items adapted from Premkumar and Roberts (1999) and Wang and Wang (2020) were used to measure the level of resource provision, the level of commitment and the level of managerial involvement to support smart city initiatives. Four items of Technological Readiness (TR), from Parasuraman (2000), Lin and Hsieh (2007), and Alsaad et al. (2017), on whether or not the organization is ready to accept new technologies, were considered. Lastly, Smart City Information System Effectiveness (SCISE) was measured using five items based on Nam and Pardo (2011), Lee et al. (2014) and Chatterjee et al. (2018) that cover system effectiveness towards the improvement of urban functionalities and citizen satisfaction with the system.

3.4. Data Analysis Technique

Analysis of the collected data was done using Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart-PLS software. As PLS-SEM can deal with complex model structures and has an acceptable performance with small and medium sample sizes, it is, therefore, very appropriate for investigating the predictive power of independent variables and the tenability of the proposed model (Sarstedt et al., 2021).

3.5. Ethical Considerations

The study was approved by the relevant institutional review board. The study's purpose, voluntary participation, and the confidentiality of responses were conveyed to

participants through a consent form. Personal information was not collected, therefore, participants remained anonymous, and their data remained private according to ethical guidelines proposed by Resnik (2015).

4. Results

This section displays analytic results attained from survey data obtained from 500 professionals participating in smart city development work. The analysis presents the results by addressing the formulated hypotheses using sequential order to evaluate CCI and BDAC relationships with SCISE alongside SI and IQ mediation effects and OS and TR moderation effects, respectively. The structural equation model's hypothesized paths, along with construct reliability assessment, are investigated through statistical tests like Convergent Validity, HTMT Ratio, and Path Analysis.

Table 1
Convergent Validity Test

Constructs	items	Loading	Alpha	CR	AVE
BDAC	BDAC1	0.794	0.876	0.906	0.618
	BDAC2	0.798			
	BDAC3	0.776			
	BDAC4	0.761			
	BDAC5	0.777			
	BDAC6	0.809			
CCI	CCI1	0.819	0.866	0.903	0.651
	CCI2	0.804			
	CCI3	0.795			
	CCI4	0.8			
	CCI5	0.814			
IQ	IQ1	0.825	0.856	0.897	0.635
	IQ2	0.817			
	IQ3	0.777			
	IQ4	0.769			
	IQ5	0.795			
OS	OS1	0.813	0.817	0.879	0.646
	OS2	0.817			
	OS3	0.837			
	OS4	0.746			
SCISE	SCISE1	0.82	0.846	0.891	0.62
	SCISE2	0.775			
	SCISE3	0.726			
	SCISE4	0.797			
	SCISE5	0.815			
SI	SI1	0.758	0.822	0.882	0.653
	SI2	0.813			
	SI3	0.841			
	SI4	0.817			
TR	TR1	0.798	0.819	0.88	0.648
	TR2	0.815			
	TR3	0.832			
	TR4	0.773			

The results of convergent validity tests for study constructs of Cloud Computing and Big Data Analytics in Smart City Information Systems appear in Table 1. Analysis results in Table 1 demonstrate that the measurement model possesses strong validity because it meets appropriate standards for loadings and internal consistency measures such as Cronbach's Alpha (α), CR Composite Reliability (CR) and AVE Average Variance Extracted (AVE) across all constructs. Only a few items are slightly below the threshold of 0.7 and yet suitable for exploratory research presented in the item loadings results of all constructs. Internal consistency stands at a good level based on Cronbach's Alpha values from 0.817 to 0.876. The constructs demonstrate reliability based on the Composite Reliability scores, which exceed 0.88. Analysis of Average Variance Extracted values demonstrates sufficient convergent validity because these values exceed the minimum threshold of 0.5 set by Fornell and Larcker (1981). The presented results demonstrate that the research instruments used in this study exhibit strong psychometric quality.

Table 2
HTMT Ratio

	BDAC	CCI	IQ	OS	SCISE	SI	TR
BDAC							
CCI	0.121						
IQ	0.595	0.498					
OS	0.436	0.514	0.58				
SCISE	0.51	0.46	0.721	0.702			
SI	0.465	0.686	0.708	0.857	0.75		
TR	0.516	0.339	0.772	0.445	0.536	0.458	

A discriminant validity check based on the Heterotrait-Monotrait (HTMT) ratios appears in Table 2. The evaluation of HTMT values should be kept below 0.85 to validate conceptual separation among constructs (Henseler et al., 2015). The results in the table show that System Integration (SI) stands as highest with a ratio of 0.857 to Organizational Support (OS) although it approaches the threshold which justifies subsequent investigation. The study demonstrates good discriminant validity between most analyzed constructs through HTMT values which fall below 0.85. The level of discriminant validity between Cloud Computing Infrastructure (CCI) and Big Data Analytics Capabilities (BDAC) is 0.121 based on their HTMT value.

Table 3
Fornell Larcker

	BDAC	CCI	IQ	OS	SCISE	SI	TR
BDAC	0.786						
CCI	-0.099	0.807					
IQ	0.518	0.43	0.797				
OS	0.364	0.435	0.488	0.804			
SCISE	0.44	0.395	0.616	0.59	0.787		
SI	0.395	0.581	0.596	0.704	0.626	0.808	
TR	0.435	0.291	0.647	0.365	0.452	0.38	0.805

Table 3 demonstrates the findings from the Fornell-Larcker criterion test that employs square root AVE values for construct assessment by measuring correlations against construct pairs (Fornell & Larcker, 1981). The square root AVE values (BDAC, CCI, IQ, OS, SCISE, SI, TR) exceed all off-diagonal correlation values in the corresponding rows and columns of Table 3. The results demonstrate acceptable discriminant validity since each construct varies more with its measurement tools than with alternative variables in the structural model.

The square root AVE of 0.786 for BDAC exceeds 0.518 which represents its maximum association with the construct IQ. The square root AVE value for TR reaches 0.805 while its highest correlation of 0.647 belongs to IQ which remains below 0.805. The distinct measurement framework shows one construct shares minimal variance with other constructs in relation to each construct dimension. This consistency pattern validates using distinct constructs in the research model.

Table 4 indicates that the cross-loadings analysis evaluated the discriminant validity of constructs and items in the research study. One attribute of item validity is called cross-loading in which the measurement indicators depict the degree of their relationship among other constructs in comparison to the construct it represents. All the survey items must be achieving their maximum level of measurement on their intended construct and have a low level of correlation with other constructs in the test. The results obtained in terms of the data outcomes imply the presence of discriminant validity because of the observed pattern. Each of the items associated with the construct of Big Data Analytics Capabilities has the highest relationship with BDAC with less strong relationships with Cloud Computing Infrastructure and Information Quality and other constructs. The statistics indicate that the items related to CCI, IQ, OS, SCISE, SI and TR have the highest loadings to their respective constructs hence validating the relationship between items and constructs. The study design is effective in preserving the specific connection models between questionnaire items and research constructs; consequently, they provide the reliability of questionnaire structure and measurement model (Hair et al., 2019).

Table 4
Cross Loadings

	BDAC	CCI	IQ	OS	SCISE	SI	TR
BDAC1	0.794	-0.099	0.39	0.332	0.36	0.304	0.336
BDAC2	0.798	-0.056	0.413	0.269	0.323	0.323	0.342
BDAC3	0.776	-0.089	0.422	0.218	0.309	0.282	0.352
BDAC4	0.761	-0.094	0.411	0.287	0.361	0.293	0.305
BDAC5	0.777	-0.047	0.395	0.299	0.389	0.299	0.367
BDAC6	0.809	-0.081	0.41	0.312	0.338	0.357	0.349
CCI1	-0.079	0.819	0.353	0.358	0.327	0.489	0.21
CCI2	-0.088	0.804	0.376	0.337	0.321	0.457	0.225
CCI3	-0.09	0.795	0.309	0.4	0.31	0.447	0.246
CCI4	-0.128	0.8	0.331	0.323	0.26	0.432	0.227
CCI5	-0.022	0.814	0.361	0.338	0.367	0.513	0.266
IQ1	0.371	0.364	0.825	0.391	0.476	0.464	0.473
IQ2	0.467	0.361	0.817	0.402	0.527	0.509	0.529
IQ3	0.458	0.32	0.777	0.425	0.487	0.529	0.515
IQ4	0.367	0.326	0.769	0.343	0.489	0.433	0.529
IQ5	0.39	0.343	0.795	0.381	0.47	0.433	0.533
OS1	0.274	0.331	0.322	0.813	0.467	0.569	0.253
OS2	0.333	0.348	0.414	0.817	0.469	0.563	0.28
OS3	0.243	0.408	0.456	0.837	0.539	0.592	0.329
OS4	0.336	0.3	0.371	0.746	0.41	0.537	0.314
SCISE1	0.394	0.335	0.528	0.522	0.82	0.527	0.419
SCISE2	0.37	0.278	0.462	0.458	0.775	0.48	0.356
SCISE3	0.271	0.338	0.449	0.413	0.726	0.451	0.271
SCISE4	0.324	0.286	0.466	0.429	0.797	0.502	0.322
SCISE5	0.366	0.318	0.512	0.492	0.815	0.5	0.398
SI1	0.334	0.404	0.451	0.478	0.497	0.758	0.254
SI2	0.291	0.531	0.478	0.58	0.496	0.813	0.343
SI3	0.312	0.483	0.489	0.636	0.521	0.841	0.324
SI4	0.34	0.455	0.508	0.575	0.51	0.817	0.304
TR1	0.377	0.205	0.504	0.353	0.367	0.318	0.798
TR2	0.32	0.208	0.525	0.257	0.348	0.251	0.815
TR3	0.325	0.329	0.542	0.303	0.407	0.366	0.832
TR4	0.385	0.177	0.512	0.258	0.326	0.277	0.773

The measurement model presented in Figure 1 reviews the relationship between Cloud Computing Infrastructure (CCI), Big Data Analytics Capabilities (BDAC), System Integration (SI), Information Quality (IQ), Organizational Support (OS), Technological Readiness (TR), and Smart City Information System Effectiveness (SCISE). The graphical representation indicates high direct relationships with CCI, and the largest impact with SI (0.627) which means that good cloud computing infrastructure is a significant contributor to system integration in smart cities. BDAC can help to enhance information quality in the smart city environment because it increases IQ by 0.566.

The data proves that the efficacy of the smart city information system is directly determined by the success of the system integration as well as by the improvement of the information quality that are rated at 0.256 and 0.239, respectively. The model represents OS and TR moderators, but their directions as represented by the values ranging between 0.076 and 0.179 have low effect on the general model. The research confirms the adequacy of the measurement model in testing the hypothesis by high level of indicator reliability indicated by high outer loading that is above the typical value of 0.70 (Sarstedt et al., 2021). These results of the research provide strong empirical support to the measured relationships in the research framework.

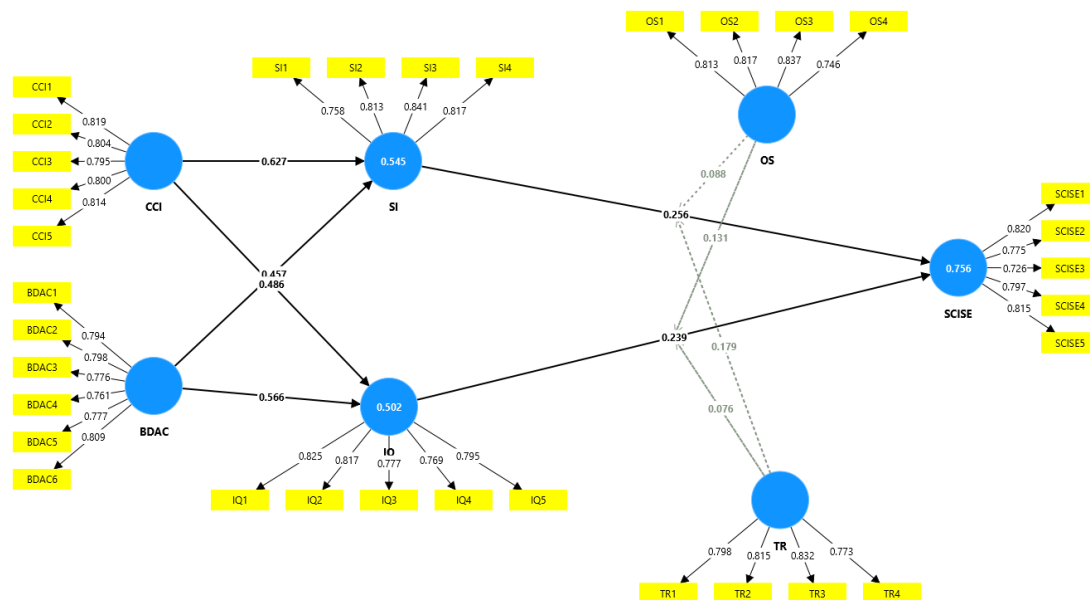


Figure 1: Measurement Model

Table 5
Path Analysis

	Original sample	Standard deviation	T statistics	P values
BDAC -> IQ	0.566	0.027	21.308	0.000
BDAC -> SI	0.457	0.028	16.106	0.000
CCI -> IQ	0.486	0.028	17.558	0.000
CCI -> SI	0.627	0.026	23.731	0.000
IQ -> SCISE	0.239	0.040	5.997	0.000
OS -> SCISE	0.251	0.033	7.693	0.000
SI -> SCISE	0.256	0.036	7.110	0.000
TR -> SCISE	0.131	0.035	3.757	0.000
TR x IQ -> SCISE	0.076	0.026	2.896	0.004
OS x IQ -> SCISE	0.131	0.033	3.991	0.000
TR x SI -> SCISE	0.179	0.036	4.999	0.000
OS x SI -> SCISE	0.088	0.024	3.585	0.000
BDAC -> IQ -> SCISE	0.135	0.024	5.686	0.000
CCI -> IQ -> SCISE	0.116	0.021	5.552	0.000
BDAC -> SI -> SCISE	0.117	0.018	6.449	0.000
CCI -> SI -> SCISE	0.160	0.024	6.588	0.000

The results from path analysis to determine direct and indirect effects and moderation between variables appear in Table 5. A statistical analysis confirms with $p < 0.01$ significance that all the proposed relationships exist as predicted. The results demonstrate that big data analytics capabilities directly affect both information quality ($\beta=0.566$, $t=21.308$) and system integration ($\beta=0.457$, $t=16.106$), showing their essential role in improving these elements. The results show that cloud infrastructure plays a vital role in information management because it leads to positive effects on both IQ ($\beta=0.486$, $t=17.558$) and SI ($\beta=0.627$, $t=23.731$). The analysis demonstrates that IQ, along with SI, produces significant positive influences on SCISE because they act as mediators ($\beta=0.239$, $t=5.997$, $\beta=0.256$, $t=7.110$). Internal organizational support (OS) and technological readiness (TR) play direct and positive roles in shaping SCISE, according to the findings (OS = 0.251, $t=7.693$; TR = 0.131, $t=3.757$). The results of moderation analysis through Cohen et al.'s (2014) method demonstrate that OS and TR increase the positive influence between IQ and SI on SCISE (Cohen, West, & Aiken, 2014). The analysis shows indirect relationships that depend on IQ and SI as both direct and indirect links for transmitting the organizational factors' influence from BDAC and CCI onto SCISE. The validated findings through these studies provide strong evidence for the conceptual model while emphasizing the need for combined analytics and infrastructure with organizational factors.

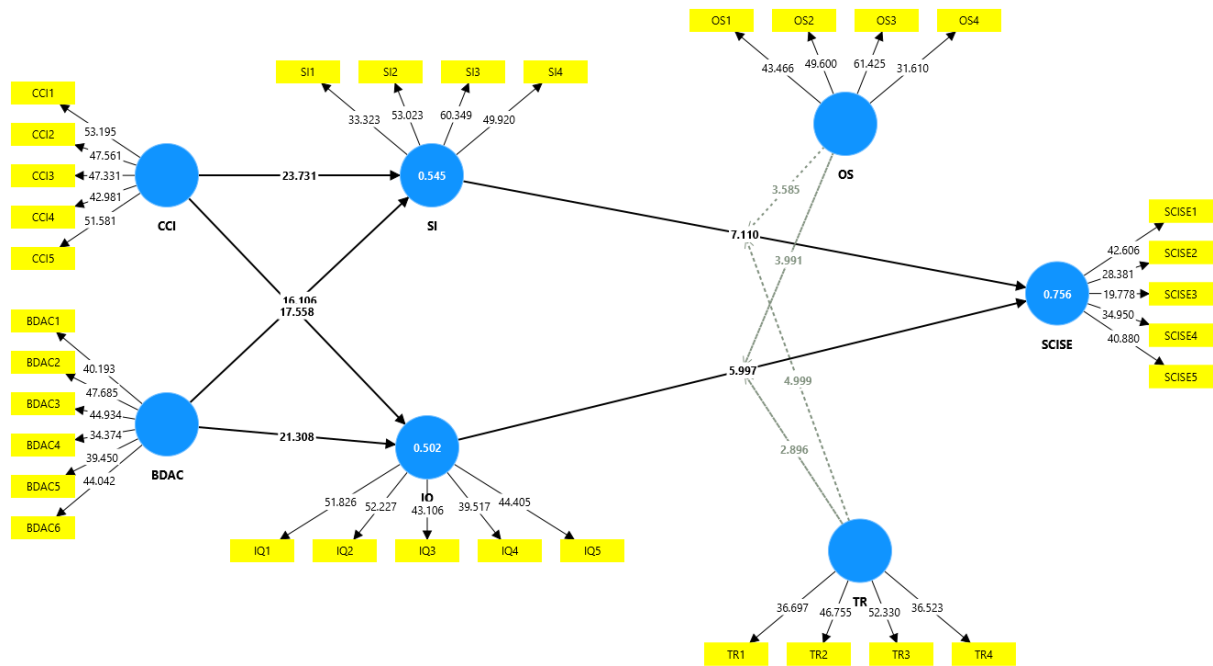


Figure 2: Structural Model

Figure 2 presents the structural model with its significance values (T-statistics) for linking constructs to each other. The paths demonstrating high statistical significance connect CCI with SI ($t=23.731$) and BDAC with IQ ($t=21.308$), according to Sarstedt et al. (2021). Evaluation of mediating links established that System Integration links to Smart City Information System Effectiveness at ($t=7.110$) and Information Quality links to SCISE outcome at ($t=5.997$) found significant results. This study strengthens theoretical assumptions by showing how Organizational Support (OS) and Technological Readiness (TR) serve as moderators that enhance the relationships between the variables.

5. Discussion

The purpose of this study was to highlight the relationships between Cloud Computing Infrastructure (CCI) and Big Data Analytics Capabilities (BDAC) for Smart City Information System Effectiveness (SCISE), mediation of Information Quality (IQ) and System Integration (SI), and moderation of Organizational Support (OS) and Technological Readiness (TR). The hypotheses were robustly supported by the findings which contributed to interesting findings that aligned to the previous research.

Previous studies have shown that BDAC has a significant positive impact on Information Quality ($\beta=0.566$), suggesting that strong analytical capabilities can help to ensure that information in smart cities is accurate, relevant, and timely (Akter et al., 2016; Gupta & George, 2016). Likewise, the effect of BDAC on System Integration ($\beta=.457$) is found to be of similar importance to ensure the incorporation of advanced analytics into the urban management systems that are complementary to what Bibri and Krogstie (2017) previously found.

Results show that CCI has a strong positive impact on both SI ($\beta=0.627$) and IQ ($\beta=0.486$), corroborating prior research, which claimed that cloud infrastructure allows data integration and real-time Information management on different urban platforms (Oliveira et al., 2014; Gangwar et al., 2015). These findings prove the theoretical proposition that the implementation of smart city solutions which are based on robust cloud architectures to deal with data complexity (Stergiou et al., 2018; Santana et al. 2017).

Results also show that high levels of SI ($\beta=0.256$) and IQ ($\beta=0.239$) significantly enhance SCISE, therefore, the integration of city-wide systems and quality data are found to be the major contributors of an effective information system (for a smart city). Given this result, it is also in line with previous work by Rai et al. (2006) and Wixom and Todd (2005),

who narrowed down the smart city investment outcomes to justify information quality and Integration.

In addition, Organizational Support was found to be a positive significant predictor of SCISE ($\beta=0.251$) signifying the importance of having organizational support to properly implement smart city technologies. However, the findings of this study are corroborated with the previously conducted research on the rudiments of technology implementation, such as managerial support, resource allocation, and a favorable organizational culture (Premkumar & Roberts, 1999; Wang & Wang, 2020). Like this, Technological Readiness moderately showed a direct positive impact on SCISE ($\beta=0.131$) in a positive way that the preparedness of urban management teams and infrastructure is significantly affecting the effectiveness of smart city system. Such results are consistent with results reported in Lin and Hsieh (2007) and Alsaad et al. (2017) and affirms the notion that the organizations being ready for technology will bring about higher technology benefits from adopting advanced digital solutions.

The substantial moderating effects of either OS or TR at the micro level give further refined information. They also enhanced the correlation of SI and IQ with SCISE which means that, the high degree of organizational support and technological preparedness increases the positive effects of the integrated systems and quality information on the overall performance of the smart city system. These moderating results confirm additional theoretical claims on contingency theory, that organizational context is an important determinant on technological outcome (Parasuraman, 2000).

Overall, these empirical findings have a significant contribution in determining the intricate interrelationships of cloud computing, analytics capabilities, integration practices, and organizational factors to establish practical useful methods of enhancing smart city efforts.

6. Conclusion, Implications, Limitations, and Future Research

The paper discusses how the Cloud computing infrastructure (CCI) and big data analytics capabilities (BDAC) can affect the effectiveness of Smart city information system (SCISE) mediated by the System integration (SI) and Information Quality (IQ) and mediation by the Organizational support (OS) and Technological Readiness (TR). The findings confirm the view that CCI and BDAC do enhance SI and IQ, which can be further linked to benefit of SCISE. In addition, OS and TR increase the relation between SB and SCISE, which means that the presence of a favorable organizational environment and qualification at a technological level is essential. This brings a new theoretical insight into the smart city system integrating technological and organizational dimensions into a coherent model that brings the whole picture of smart city performance.

Practically speaking, the research offers practical implications to policy makers, city planners, and administrators of smart cities. Investments in cloud infrastructure and advanced analytics should be expanded with powerful integration strategies and good information quality practices. In that case, it is also true that organizations need to be investing in expanding the internal support mechanisms and in creating a technology ready culture, which is capable of all the perks that digital transformation offers. The model of the study is good and is constrained by the fact that it is cross-sectional and based on the purposive sampling. Further studies might need to use longitudinal research or cross-country comparisons to enhance the generalizability. Secondly, variables like citizen engagement or governance structure can be used to bring out a more in-depth insight on variables that influence the success of a smart city system.

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