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The Design of a Service-Level Architecture for Handling Big Data Using Mobile Cloud Computing and the Internet of Things -AOS

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Abstract: The rapid and continuous expansion of interconnected devices equipped with sensors and actuators, utilizing diverse technologies, has led to an exponential increase in data generation. Effectively storing and processing this vast amount of data necessitates advanced computational resources, which can be provided by mobile cloud computing systems. The evolution of the Internet of Things (IoT) has facilitated machine-to-machine communication, allowing extensive data collection and prolonged storage for processing using robust cloud-based applications and big data analytics. However, there is currently no established method for managing the enormous volume of data generated by IoT devices in a way that enables seamless communication in both real-time and non-real-time contexts. This results in challenges related to heterogeneity and interoperability. Addressing this issue requires the development of a reference architecture that integrates big data, mobile cloud computing, and IoT, fostering device interoperability and heterogeneity. The proposed service-level architecture aims to unify these technologies, demonstrating their interaction and facilitating scalability, integration, and interoperability across various services. Ultimately, this architecture will provide an innovative approach to handling big data within mobile cloud computing and IoT environments, ensuring seamless communication among devices from different manufacturers.

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I. INTRODUCTION

This chapter explores the convergence of big data, mobile cloud computing (MCC), and the Internet of Things (IoT) by analyzing their definitions, operational frameworks, and applications. It examines existing reference architectures that support the integration of these technologies, providing both theoretical and empirical insights. This review serves as the foundation for developing a novel architecture tailored to managing big data through MCC and IoT, addressing contemporary technological challenges and opportunities. Additionally, this chapter defines key concepts essential for understanding big data within the context of mobile cloud computing. The rapid adoption and expansion of cloud technology in 2022 have led to the emergence of numerous cloud computing service providers offering various cloud-based solutions. These services range from on-demand applications to database storage and other virtualized IT resources, eliminating the need for organizations to manage infrastructure-related tasks such as installation, updates, backups, and security.

II. PROBLEM STATEMENT

The tremendous continued increase in the interconnection of various devices fitted with sensors and actuators, utilizing diverse technologies, results in the generation of vast amounts of data. This data requires significant storage and processing capabilities, which mobile cloud computing systems can provide. The rise of the Internet of Things (IoT) has accelerated research into machine-to-machine communication, enabling extensive data collection and long-term storage for cloud-based big data processing. However, a major challenge remains: there is no standardized method to manage the enormous data volumes produced by IoT in a way that ensures seamless communication in both real-time and non-real-time scenarios. This leads to issues related to heterogeneity and lack of interoperability.

To address this, it is essential to design a reference architecture that enables the effective handling of big data through the integration of Mobile Cloud Computing (MCC) and IoT. This integration will enhance device interoperability and heterogeneity. The primary benefit of this study is that the proposed service-level architecture will unify big data, MCC, and IoT, illustrating their interconnections and achieving integration, heterogeneity, scalability, and

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interoperability across various services. Ultimately, the designed architecture will facilitate the seamless management of big data using MCC and IoT, ensuring device interoperability across different manufacturers and contributing to the scalability and efficiency of emerging technologies.

A. NIST Cloud Computing Reference Architecture

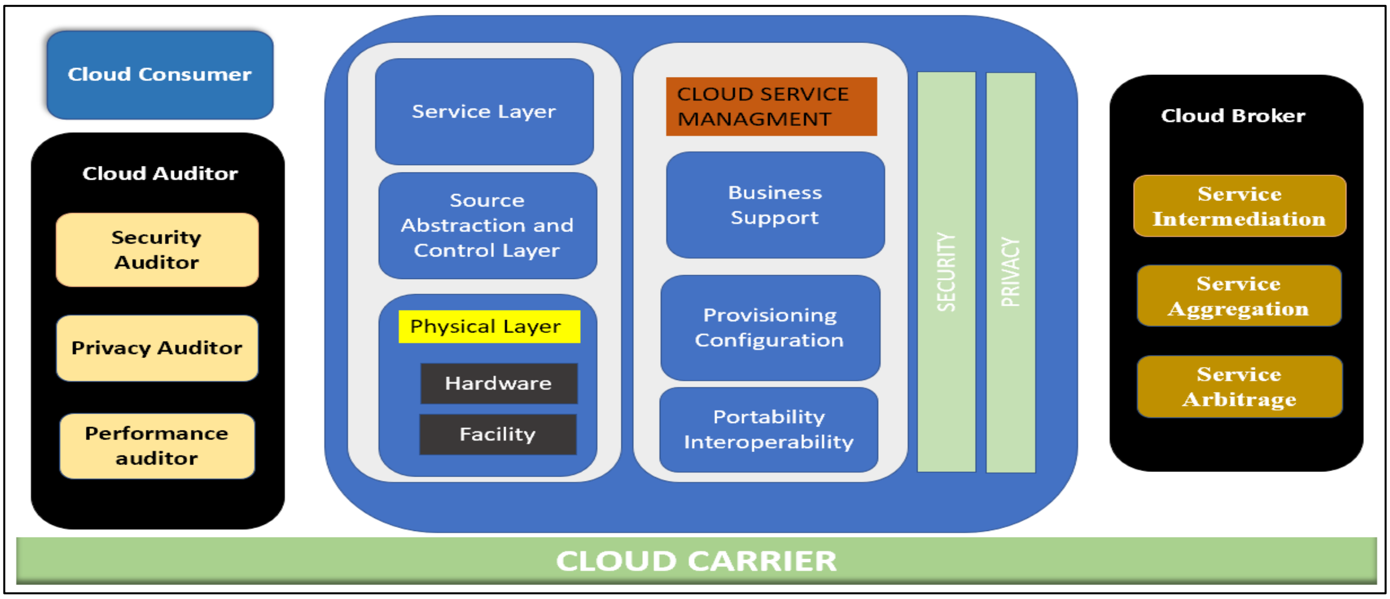

Fig 1: NIST Cloud Computing Reference Architecture

The National Institute of Standards and Technology (NIST) cloud computing reference architecture primarily focuses on defining the requirements of cloud service providers rather than their implementation. However, it emphasizes essential aspects such as portability, interoperability, and security, along with guidelines and standards, as illustrated in Figure 1. This architecture identifies five key actors: cloud consumers, cloud carriers, cloud brokers, cloud auditors, and cloud providers. Additionally, it outlines three service models: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). (NIST Cloud Computing Reference Architecture, 2011)

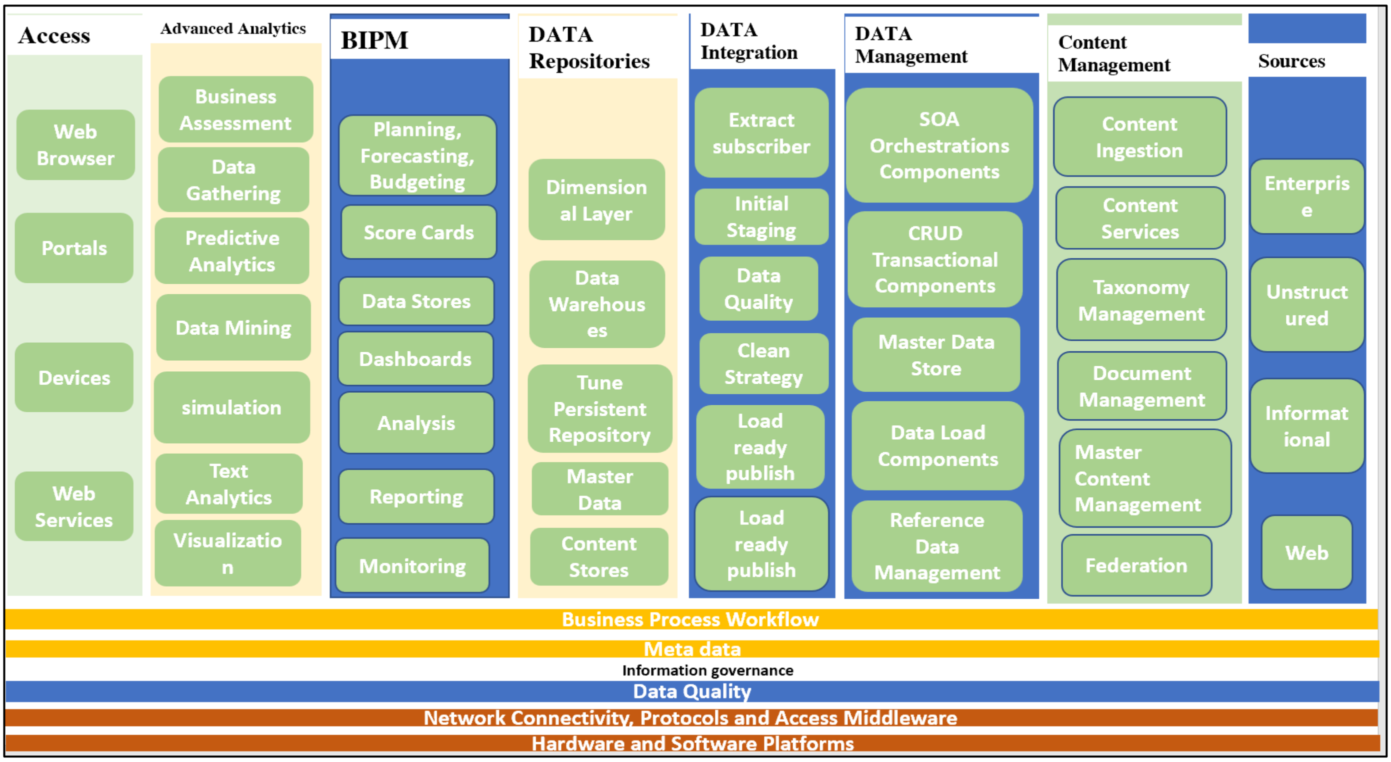

Fig 2: The IBM Business Analytics and Optimization Reference Architecture

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IBM's architecture supports processing large volumes of both structured and unstructured streaming data, including video, television broadcasts, audio, emails, chat messages, and transactional data. It serves as a guide for IBM sales, services, and professionals engaged in designing and deploying big data and analytics solutions. The architecture categorizes IBM software products based on their capabilities within a big data and analytics framework, as depicted in Figure 2. Furthermore, it provides a platform for executing applications that filter and analyze data. It supports continuous data integration from sources such as data warehouses, cloud storage, and databases, allowing real-time updates without requiring system restarts. Additionally, it enables data integration by facilitating access to heterogeneous data sources, ensuring seamless retrieval regardless of location, format, or vendor. (Analytics, 2016)

B. Oracle Big Data Reference Architecture

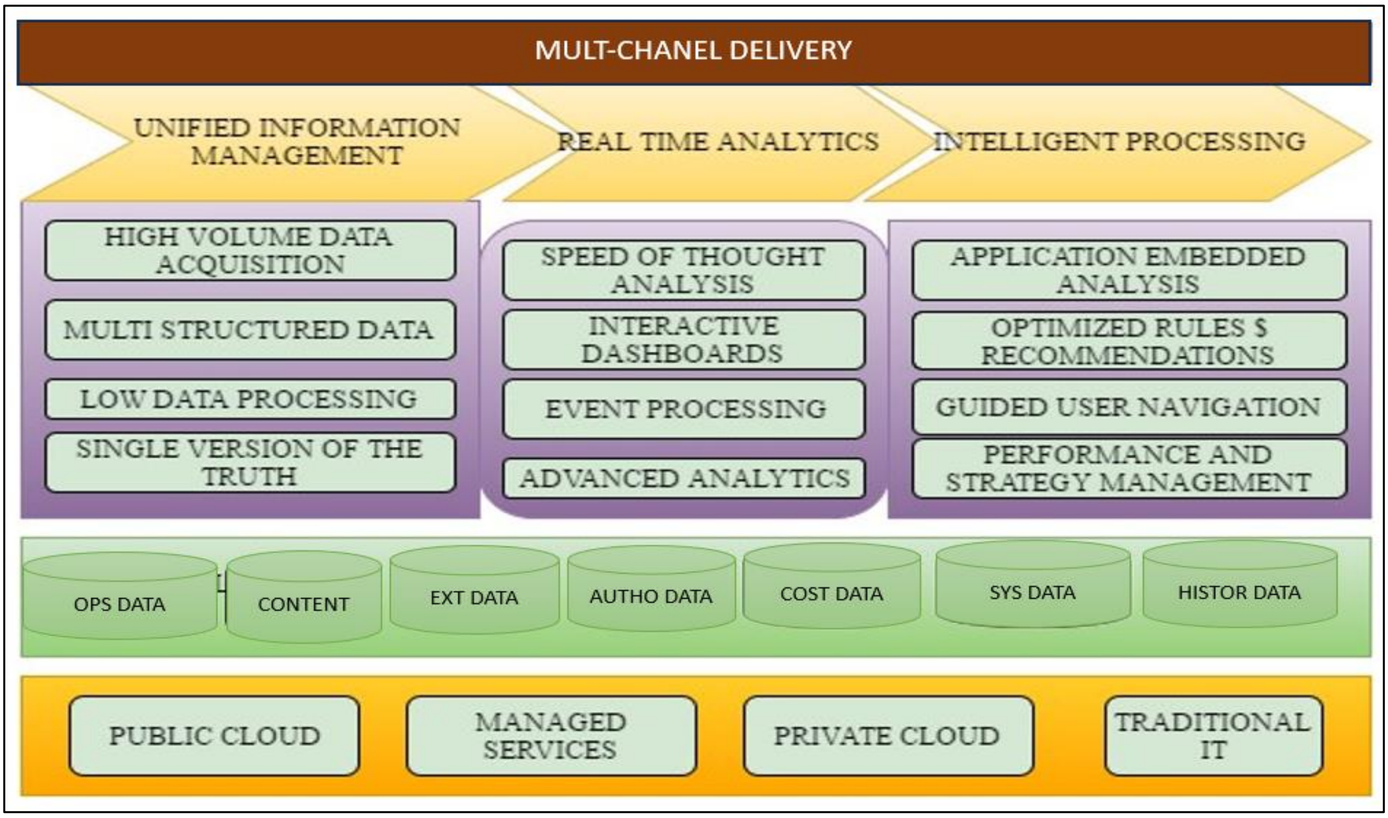

Fig 3: Big Data & Analytics Reference Architecture

The architecture shown in Figure 3 above uses capabilities to provide a high description of the big data and data analysis solution so as to accomplish its major objective of attaining high performance and scalability.

C. Big Data Ecosystem Architecture

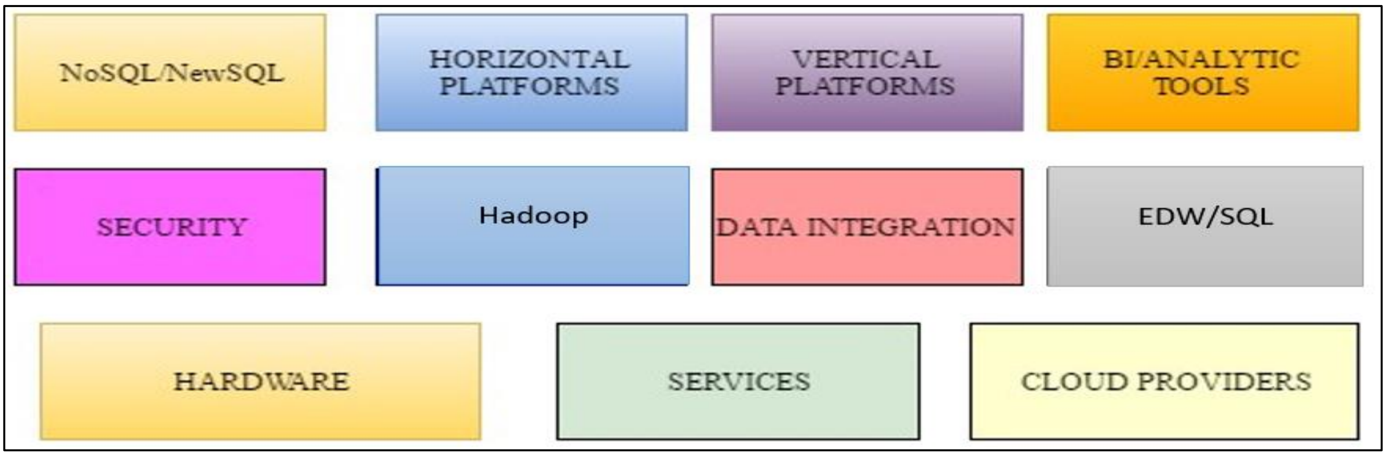

Fig 4: Big Data Ecosystem Architecture

Figure 4 shows the broad view of the variety of data stores for different data structures, different methods of search and query, and different algorithms and approaches to analyse, store, and recombine both structured and unstructured data. It discusses the main capabilities required for a more scoped view of Big Data, it also indicates the broad set of capabilities of the Big Data Ecosystem, technologies. (The Open Group, 2016)

D. The Reference Architecture

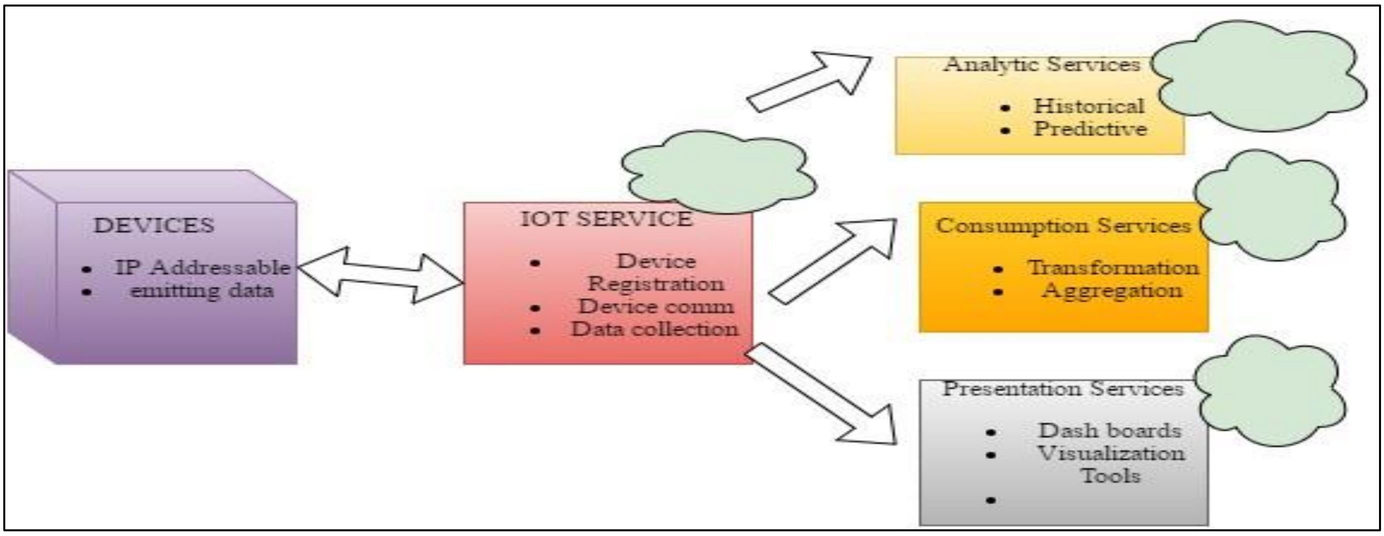

Fig 5: IOT Reference Architecture

The Internet of Things at a very high level is not complicated. It all comes down to data, lots of data. By 2020 there will be hundreds of billions of devices connected to the internet and feeding exabytes of data to the cloud daily. It is the software that we create that will take that data and turn it into business insight.

Figure 5 therefore focuses on options for dealing with the massive amount of data that comes streaming in from connected devices. (Sqrrl"s Take on the Big Data Ecosystem, 2016)

E. TMF Big Data Analytics Reference Architecture

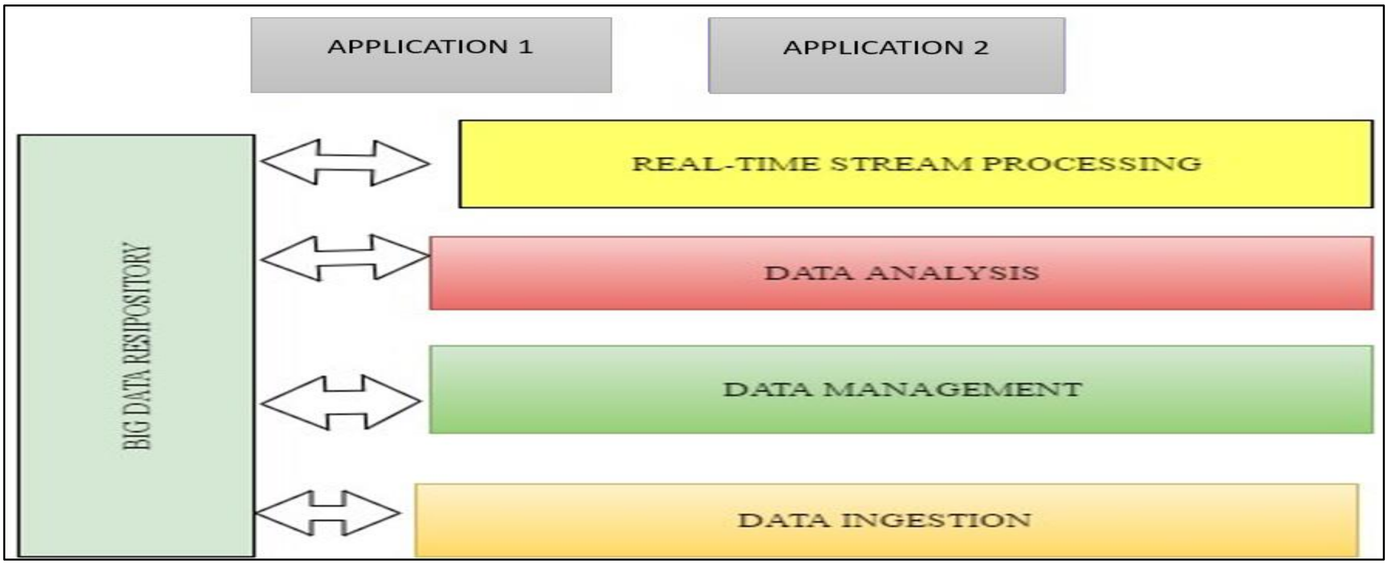

Fig 6: TMF Big Data Analytics Reference Architecture

Figure 6 illustrates an architecture which provides lower cost effective for data storage with better processing mechanism which has led to add value to existing data.

It is a standard architecture for handling data ingestion, data management, data analysis and real time stream processing being accessed in the big data repository.

It is a streaming analytics platform that combines real-time streaming, discovery, analysis, visualization, and action, which drastically improves the high performance of the system and supports the scalability of devices connected to it from different developers.

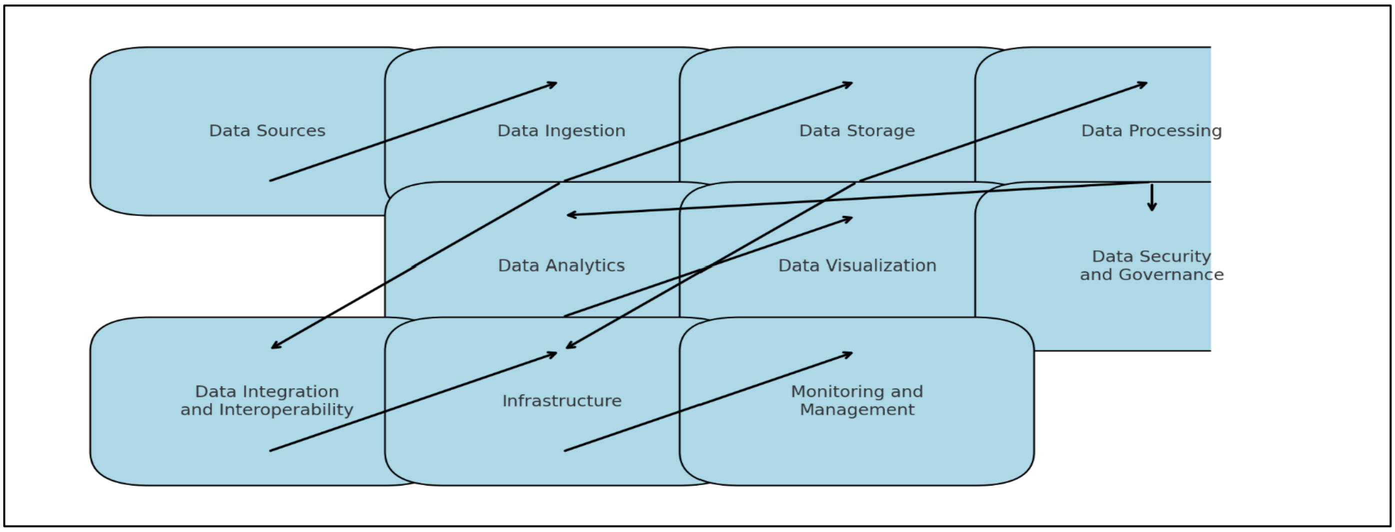

Fig 7: Big Data Reference Architecture

Most Big Data projects use variations of Big Data reference architecture. Understanding the high-level view of this reference architecture provides a good background for understanding Big Data and how it complements existing analytics, big data intelligence, databases and systems. This architecture is not a fixed, one-size-fits-all approach. Each component of the architecture has at least several alternatives with its own advantages and disadvantages for a particular workload. Companies often start with a subset of the patterns in this architecture, and as they realize value for gaining insight to key business outcomes, they expand the breadth of use. (Daniel, 2017)

III. RESEARCH METHODOLOGY

A. Data Collection Methods and Instruments

➢ *Questionnaire*

A questionnaire is a structured tool designed to gather data on a research problem, aligning with the study's objectives (Al Amin, 2020). In this study, both open-ended and close-ended questionnaires were distributed to AOS Ltd staff to collect quantitative insights on designing a service-level architecture for big data management through mobile cloud computing and IoT.

➢ *Interview Guide*

An interview guide comprises pre-formulated questions used during structured discussions. Interviews facilitate a two-way exchange of ideas, allowing responses tailored to the interviewee's knowledge and expertise. (Wellman & Kruger, 2019; JA, 2018)

➢ *Data Processing*

Python serves as a robust tool for data analysis. This study utilizes Python libraries such as Pandas for data cleaning, NumPy and SciPy for mathematical transformations, ensuring efficient big data processing within the research framework.

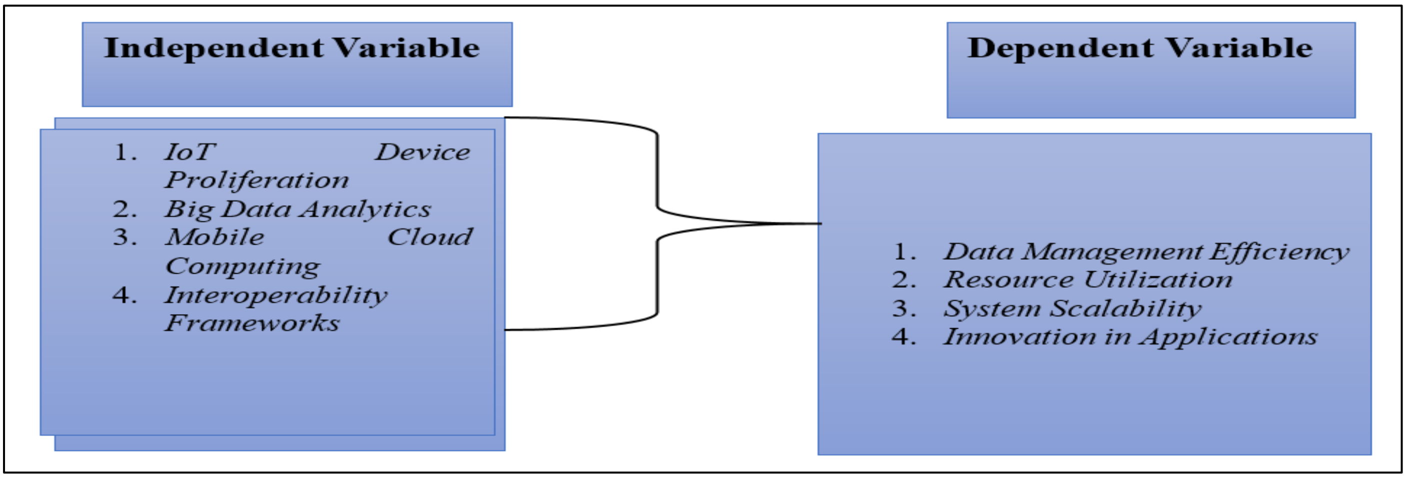

Fig 8: Conceptual Framework

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IV. PRESENTATION AND ANALYSIS OF RESEARCH FINDINGS

This study's findings are examined and interpreted based on its clearly defined objectives: designing a robust service-level architecture capable of efficiently managing the massive data influx from IoT devices and mobile cloud computing systems, developing advanced security measures to safeguard data integrity, confidentiality, and privacy, and optimizing the architecture to enhance resource utilization and operational efficiency.

A. Data Visualization

Data visualization refers to the graphic representation of information and data. It uses visual components such as charts, graphs, and maps to provide an accessible way to examine and understand trends, outliers, and patterns in data. By transforming raw data into a visual format, it helps identify key insights and facilitates decision-making.

B. Respondents' Demographic Profiles

The researcher began the data analysis by focusing on the background characteristics of the respondents. These profiles are based on factors such as service-level architecture skills, abilities, age, gender, and years of experience. By understanding these demographic characteristics, a more comprehensive interpretation of the data can be made.

C. Respondents' Age

Analyzing the age of respondents is crucial for understanding the demographic makeup of the survey sample. Age data provides valuable insights into generational trends, preferences, and behaviors. It allows for the profiling of respondents into distinct generational cohorts, which can be useful in various domains such as marketing, policy planning, and behavioral analysis. By analyzing these age-related trends, the study can uncover potential correlations and patterns that might influence the design and functionality of the service-level architecture.

D. Importance of Data Visualization in This Context

The use of data visualization tools is critical in this context, as it aids in presenting complex information in an easily understandable format. Through the visualization of respondents' age, experience, and other demographic data, the researcher can identify patterns and outliers that would otherwise be difficult to detect. This helps in drawing meaningful conclusions and tailoring the architecture to meet the needs and preferences of the targeted user groups.

➢ *Distribution of Respondents by Age*

Table 1: Distribution of Respondents by Age

		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	18-30	160	73.7	73.7	73.7
	31-45	40	18.4	18.4	92.2
	46-55	10	4.6	4.6	96.8
	55-65	7	3.2	3.2	100.0
	Total	217	100.0	100.0	

The age distribution of employees in the IT sector reveals a diverse workforce. A significant majority, 73.7%, are in the 18-30 age range, highlighting a strong presence of younger, tech-savvy professionals who contribute innovation and adaptability to the organization. The 31-45 age group follows with 18.4%, representing a notable proportion of mid-career professionals who bring valuable experience. In contrast, the 46-65 age range makes up 7.8%, consisting of experienced employees who contribute their knowledge and expertise to data center operations. This distribution shows a balanced mix of youthful innovation and seasoned experience within the workforce.

➢ *Distribution of Respondents by Qualifications*

Table 2: Distribution of Respondents by Qualifications

		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	A1	100	46.1	46.1	46.1
	Bachelors	92	42.4	42.4	88.5
	Masters	15	6.9	6.9	95.4
	PHD	10	4.6	4.6	100.0
	Total	217	100.0	100.0	

The educational background of respondents across various sectors shows a diverse distribution. A significant majority, 88.5%, hold undergraduate qualifications, with 46.1% having an A1 level and 42.4% holding bachelor’s degrees. This indicates a solid foundation of technical knowledge and skills among employees. Additionally, 6.9% of respondents have attained a master's degree, and 4.6% hold a PhD. This suggests a notable presence of highly educated employees, which contributes specialized expertise and leadership within the organization. The presence of educated individuals enhances the accuracy and quality of the data, ensuring that the responses gathered are reliable and can inform the development of effective solutions for the community. Distribution of Respondents by Experience.

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Table 3: Distribution of Respondents by Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	30	13.8	13.8	13.8
	1-2 years	71	32.7	32.7	46.5
	3-5 years	91	41.9	41.9	88.5
	More than 5 years	25	11.5	11.5	100.0
	Total	217	100.0	100.0	

The experience levels of respondents in the domain exhibit a varied distribution. Around 13.8% have less than one year of experience, representing individuals who are still becoming acquainted with the field. Approximately 32.7% have 1-2 years of experience, indicating a growing group of early-career professionals. The largest segment, 41.9%, has 3-5 years of experience, which reflects a significant number of mid-career professionals with a solid foundation in the field. Finally, 11.5% of respondents have more than 5 years of experience, showcasing a smaller but highly experienced group that is likely contributing valuable expertise and leadership within the organization.

E. Relationship of Respondent's Age and Experience Matter Tests of Between-Subjects Effects

Table 4: Relationship between Age and Experience

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.701[a]	.492	.489	.51628
a. Predictors: (Constant), How many years of experience do you have in managing mobile cloud computing systems?				

Table 5: Correlation Significant

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	55.459	1	55.459	208.068	.000[b]
	Residual	57.306	215	.267		
	Total	112.765	216			
a. Dependent Variable: Respondent's age						
b. Predictors: (Constant), How many years of experience do you have in managing mobile cloud computing systems?						

Correlations				
mexe			**How can the architecture be optimized to enhance resource utilization and operational efficiency?**	**How can a robust service level architecture be designed to effeciently handle the massive data influx from IoT devices and mobile cloud computing systems?**
Kendall's tau_b	How can the architecture be optimized to enhance resource utilization and operational efficiency?	Correlation Coefficient	1.000	.636**
		Sig. (2-tailed)	.	.000
		N	217	217
	How can a robust service level architecture be designed to effeciently handle the massive data influx from IoT devices and mobile cloud computing systems?	Correlation Coefficient	.636**	1.000
		Sig. (2-tailed)	.000	.
		N	217	217
Spearman's rho	How can the architecture be optimized to enhance resource utilization and operational efficiency?	Correlation Coefficient	1.000	.658**
		Sig. (2-tailed)	.	.000
		N	217	217
	How can a robust service level architecture be designed to efficiently handle the massive data influx from IoT devices and mobile cloud computing systems?	Correlation Coefficient	.658**	1.000
		Sig. (2-tailed)	.000	.
		N	217	217
**. Correlation is significant at the 0.01 level (2-tailed).				

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This table indicates that the Correlation Coefficient of 0.636 demonstrates a strong positive correlation between the two variables. This suggests that efforts to optimize resource utilization and operational efficiency are closely aligned with the design of robust service-level architectures for handling IoT and mobile cloud data. The Significance (p-value) of 0.000 indicates that the correlation is statistically significant at the 0.01 level, meaning that the observed relationship is unlikely to be due to chance.

Additionally, based on the Spearman's rho Correlation Coefficient of 0.658, there is a slightly stronger positive correlation compared to Kendall's Tau-B. This reinforces the strong relationship between the two questions. The Significance (p-value) of 0.000 further confirms the statistical significance of the correlation, indicating a high level of confidence in the observed linkage.

Interpreting this interdependency between the objectives: the results reveal that enhancing resource utilization and operational efficiency is intrinsically tied to designing robust architectures for handling the large data influx from IoT and mobile cloud systems. Improvements in one area, such as operational efficiency, are likely to lead to advancements in the other, like the robustness of the architecture. This highlights the interconnectedness of these factors in creating an effective system.

Refined data analysis insights and correlations further illustrate the importance of addressing both optimization and robustness simultaneously to achieve an efficient and scalable service-level architecture.

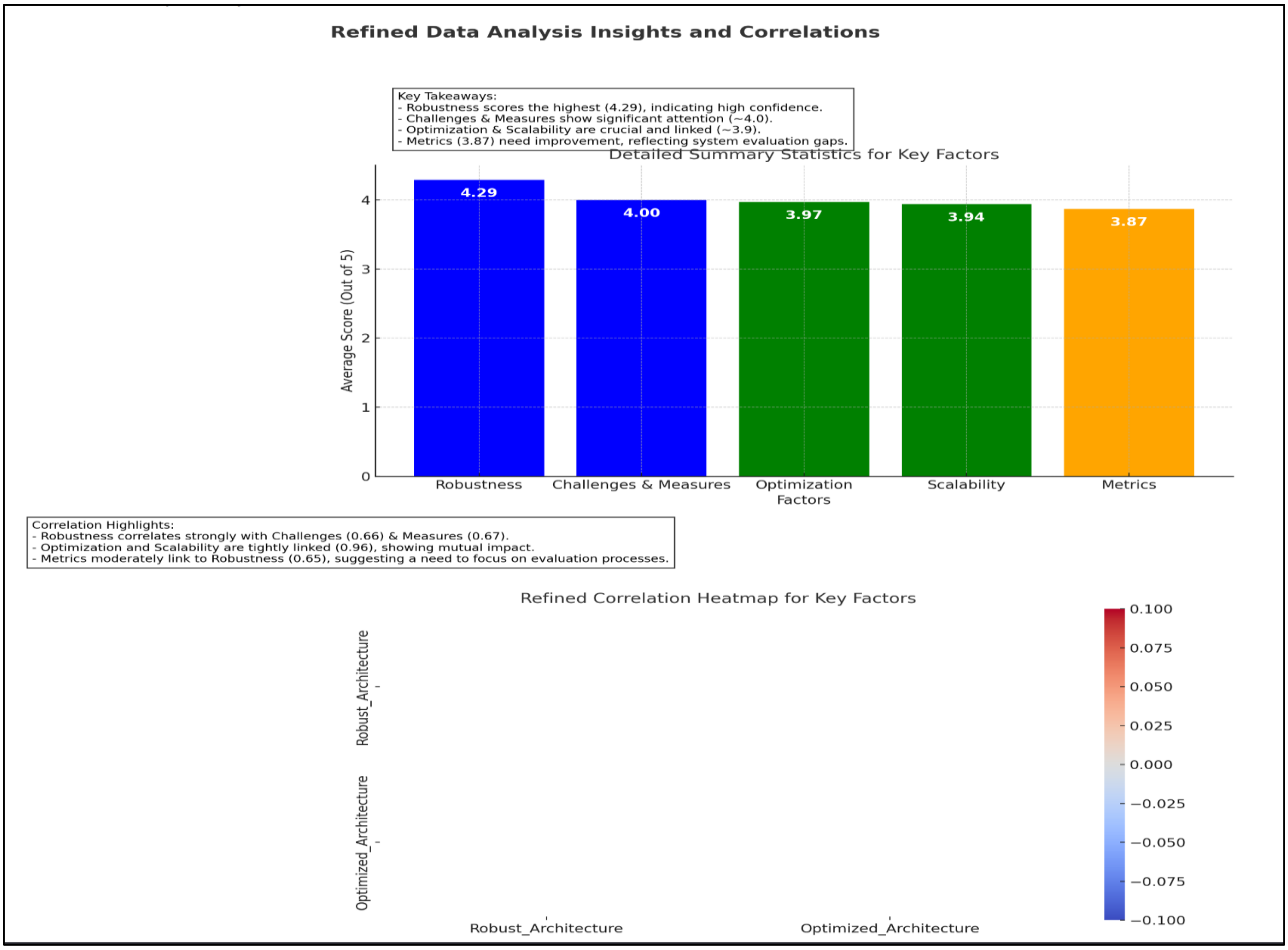

Fig 9: Summary Architecture

Based on the above graph shows that Robustness is the highest-rated aspect (4.29), reflecting strong confidence in the system's robustness. Challenges and Measures are well-addressed (~4.0).and Optimization and Scalability are viewed as crucial and closely linked (~3.9). Metrics, with the lowest score (3.87), highlight the need for better evaluation and system assessment mechanisms. This means Robustness is strongly correlated with Challenges (0.66) and Measures (0.67), suggesting their importance in creating a robust architecture. so optimization and Scalability (0.96) are interdependent, emphasizing the need for integrated strategies. for metrics moderately correlate with Robustness (0.65), underscoring the role of effective evaluation in improving overall system performance.

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F. Cross Tabs Results

Table 6: Table Shows Number of Respondents and their Opinion with their Respective Numbers and Departments

What evaluation metrics and benchmarks can be established to assess the performance, scalability, and reliability of the proposed architecture in real-world scenarios?: Total					
Count					
		How can a robust service-level architecture be designed to effeciently handle the massive data influx from IoT devices and mobile cloud computing systems?			Total
		Neutral	Effectively	Very effectively	
Please specify your role or job title within the organization?	Help Desk/ QA	15	0	0	15
	Datacenter Administrator	2	23	0	25
	Network Administrator	0	10	0	10
	Customers	0	87	70	157
	Cybersecurity	0	0	10	10
Total		17	120	80	217

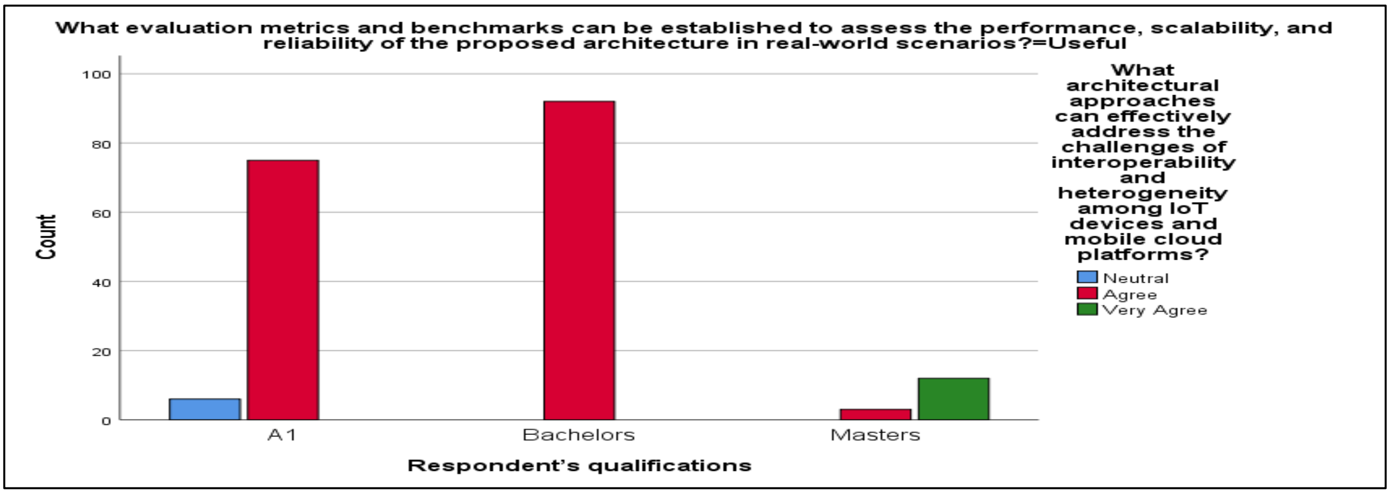

Fig 10: Respondents with Qualifications

From the above figure 10. highlights the importance of evaluation metrics and architectural approaches for addressing challenges in IoT and mobile cloud systems, analyzed across respondent qualifications (A1, Bachelors, and Masters). Respondents with higher qualifications (Masters)

➢ *Interaction between BD, MCC&IOT*

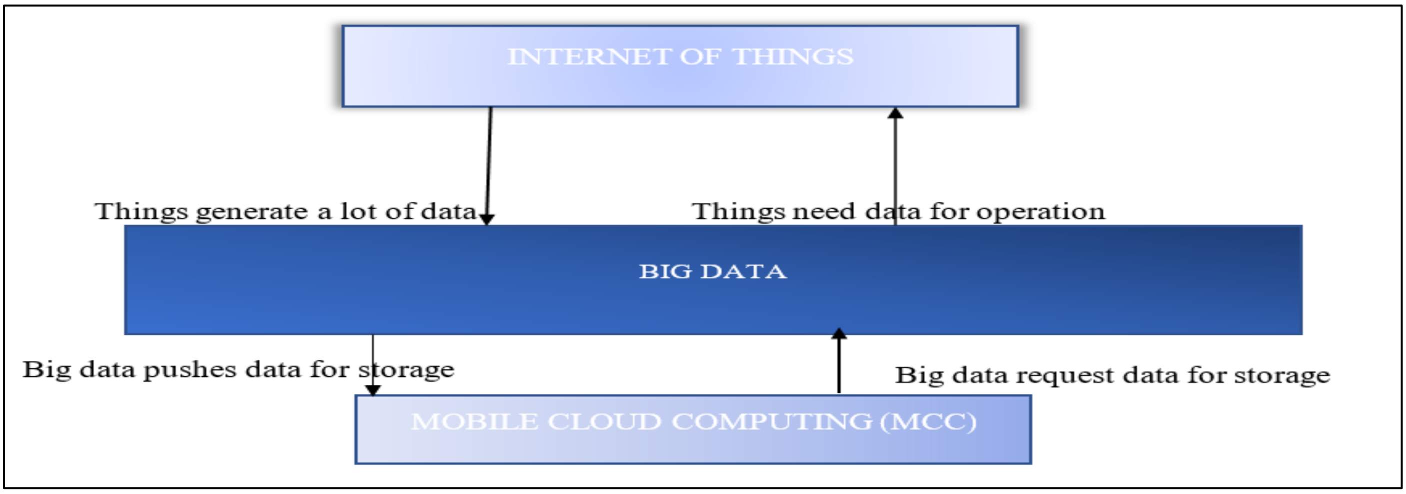

Fig 11: Interaction between BD, MCC & IOT

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Internet of things generate and produce data through the use of Actuators and sensors; however, they have limited storage capacity and low processing power so they use the services of the Big Data system to store and process the data that will be stores in the cloud and accessed by mobile devices in various applications. It is also imperative to say that mobile devices that use data from the cloud computing will also need the storage and processing power of the big data and in the end, they may be termed as Internet of things. These three technologies are interdependent and they thus need to collaborate and interoperate so as to integrate their functionalities while communicating with efficiency.

➢ *Big Data Classifications*

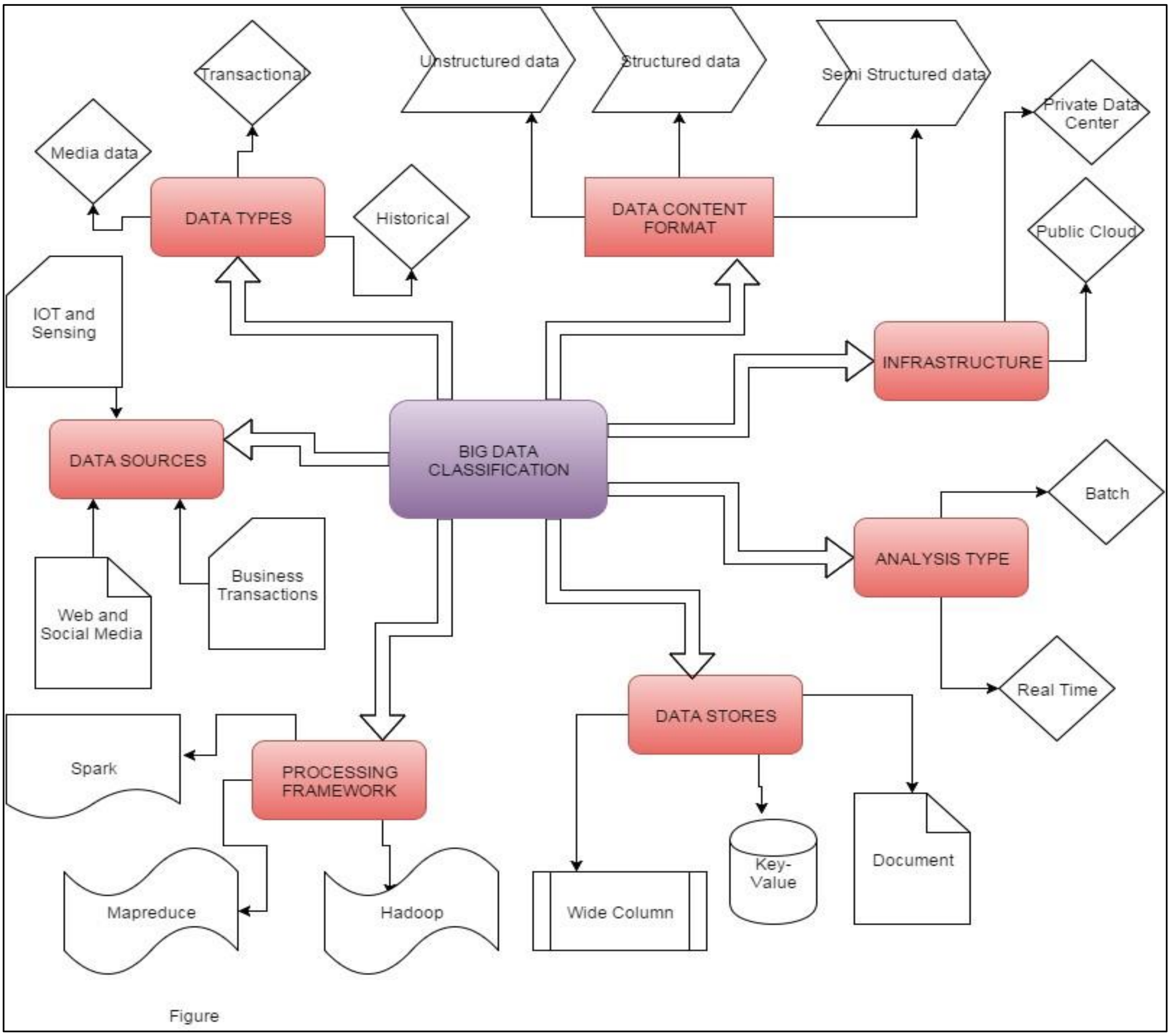

Fig 12: Big Data Classifications

➢ *Data Sources*

Web Data & social media Web pages, blogs and online articles are the sources of both structured and unstructured data that include text, videos and images.

Messaging services and status updates in social media are some of the data types from social interaction.

Proposed Big data architecture

➢ *Introduction*

Figure 13 represents the proposed architecture design for handling big data using Mobile Cloud Computing (MCC) and the Internet of Things (IoT). The components and layers of the architecture are thoroughly explained. This design is unique because it integrates three emerging technologies—Big Data (BD), MCC, and IoT—highlighting their interdependence. The integration of these technologies is essential, as each one cannot function optimally without the others.

The architecture fosters collaboration among these technologies while ensuring high security and effective management of resources and services. As a result, the designed architecture enables high performance by efficiently accommodating the heterogeneity of various components, which ultimately supports the seamless interoperability of services.

This architecture is designed to be open and flexible, able to integrate with any technology, policies, and standards. It is adaptable to various products and services from diverse audiences, as it employs Open System Interconnection (OSI) protocols and adheres to the regulations and guidelines established by international standards organizations. This openness ensures that the architecture remains scalable and can evolve as new technologies emerge.

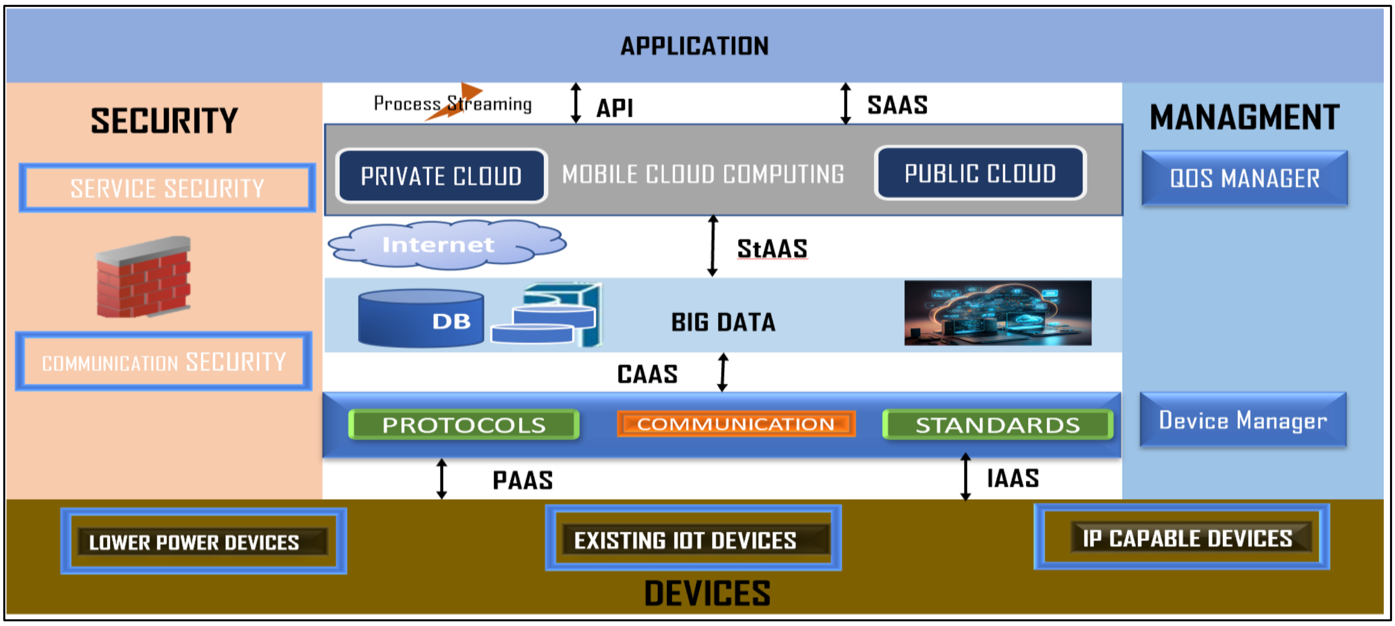

Fig 13: A Service Level Big Data Architecture using MCC and IOT

G. Key Features of this Service Lever Architecture:

- **Device Layer**: Supports **low-power IoT devices**, **existing IoT devices**, and **IP-capable devices**, allowing interoperability across heterogeneous hardware and Standardization of protocols and communication ensures that devices, regardless of their manufacturer, can seamlessly communicate Communication stack.

This model aims at mimicking the ISO/OSI stack, but it puts the focus on IoT systems requirements and characteristics IoT communication stack.

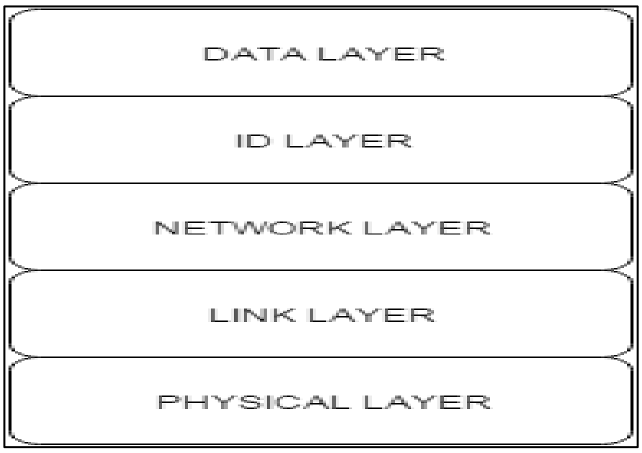

Fig 14: Communication Stack

The model illustrated in Figure 14 highlights the importance of the layers above the link layer. One of the core strengths of this communication model lies in its ability to ensure interoperability between diverse networks. The subsequent sections provide details on the various layers, explaining how each is designed to meet specific requirements of the reference model.

- **Physical Layer**: The physical layer remains consistent with the OSI model definition, which is critical to ensure that no technology is excluded, and that emerging solutions can still be integrated into the reference framework.

H. Performance of the Designed Architecture

The architecture designed to handle big data using IoT and MCC is built to address input and output bottlenecks, as it is highly data-intensive and capable of processing large volumes of data from multiple applications. By integrating emerging technologies, the architecture facilitates smooth collaboration among different services, ensuring interoperability across devices and accommodating diverse and substantial data flows. This design adheres to most established standards, protocols, and policies, making it a convenient and effective solution for its target audience to adopt in their business strategies.

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V. CONCLUSION

A service-level architecture for managing big data using Mobile Cloud Computing (MCC) has been developed, as outlined in this research. The integration of Big Data, MCC, and IoT is effectively achieved, with the architecture demonstrating how these technologies collaborate. It also clearly defines the services at each communication level. This solution addresses existing challenges faced by organizations, particularly Data Center teams, who are managing critical systems and dealing with the consumption of server resources by various services.

The architecture is designed for use by producers of different devices. Once connected to various internet networks, these devices generate vast amounts of data that will be managed and stored in the cloud. Mobile devices will then be able to access this stored data, leading to efficient service operations and enhanced security.

It is important to note that by adopting this architecture, organizations will have a unified platform for their products, allowing for better interoperability and heterogeneity. As services operate across this architecture, improvements in efficiency, performance, data management, storage, and security will be realized. The standardized guidelines and universal addressing will facilitate the smooth integration of Big Data, MCC, and IoT technologies.

RECOMMENDATIONS

The researcher suggests that this architecture will not only benefit organizations and institutions with data centers but will also be easy to implement. By defining different functions across the architecture's layers, various users and producers can introduce their products at minimal costs, utilizing low-power technologies that help conserve resources and reduce spending.

As the relationship between Big Data, MCC, and IoT continues to evolve, this reference architecture remains adaptable. It is an open system that can accommodate future technological advancements and improvements. However, given its open architecture, security measures must be implemented to ensure that only authenticated producers can connect and contribute.

REFERENCES

[1]. (n.d.), S. (2020). *biggest-cloud-security-concerns*. Retrieved from www.statista.com: https://www.statista.com/statistics/1172265/biggest-cloud-security-concerns-in-2020

[2]. AEPONA. (2010). *Mobile Cloud Computing Solution Brief*. white paper.

[3]. Al Amin, M. &. (2020). The Examination System in Bangladesh and Its Impact. *Creative Education*, Language Testing in Asia, 8, 4.

[4]. Amazon. (2015). Cloud Provider.

[5]. Analytics, I. B. (2016, May 10). *356*. Retrieved from www-01.ibm.com: http://www-01.ibm.com/software/data/infosphere/bigdataanalytics.html

[6]. (2013). *Big Data & Analytics Reference Architecture.* september: Oracle white paper.

[7]. Cavelty, M. D. (2002). *Study of the information revolution and a changing operating environment.* Wenger, Andreas: Forschungsstelle für Sicherheitspolitik und Konfliktanalyse, ETH Zürich.

[8]. Creswell, J. W. (2018). Qualitative, Quantitative, and Mixed Methods Approaches. *Sage Publications*, 5th ed.

[9]. D.A Reed, D. G. (2012). Imagining the Future: Thoughts on Computing. *Computer, vol. 45, no. 1*, pp. 25-30.

[10]. Daniel, P. a. (2017). *Reference Architecture and Classification of Technologies.* stanford article publisher.

[11]. Darton, J. (2011). NIST cloud computing Reference Architecture. *NIST Special Publication*, 500-292.

[12]. Doe, S. &. (2017). *Several Architectures and Frameworks.*

[13]. Federal. (2021, September 19). *Cloud Computing Strategy*. Retrieved from cio.gov: https://www.cio.gov/documents/Federal-Cloud-ComputingStrategy.pdf

[14]. Forum. (2016, March 26). *mobile cloud computing available*. Retrieved from mobilecloudcomputingforum: http://www.mobilecloudcomputingforum.com/

[15]. G., B. A. (2016). ELEMENTARY STATISTICS. *Community College of Allegheny County*, 14.

[16]. Grove, B. a. (2003). Research design. *Unisa Institutional Repository*, Parahoo 1997:142.

[17]. Hayles, W. (2016, March 16). *why big data and internet of things are perfect*. Retrieved from datamation.com: http://www.datamation.com/applications/why-big-data-and-the-internetof-things-are-a-perfect-match.html

[18]. Heale, R. a. (2015). *Reliability in Quantitative Studies*. Retrieved from ebn.bmj.com: https://ebn.bmj.com/content/ebnurs/18/3/66.full.pdf

[19]. JA, N. P. (2018). The interview reports from members of BoM. *Greener Journal of Educational Research*.

[20]. Laney, D. (2012, January). *Application Delivery Strategie*. Retrieved from blogs. gartner. Com: http: // blogs. gartner. Com / douglaney /files /2012/01/ ad949-3D Data-Management-Controlling-Data-Volume-Velocity-andVariety.pdf

[21]. Manz, E. &. (2017). Exploratory Study. In T. W. Edgar, *Research Methods for Cyber Security* (pp. 95-130). vancouver: 10.1016/B978-0-12-805349-2.00004-2.

[22]. Mell, P. a. (2019). *Energy Aware Processor Architecture for Effective Scheduling and Power Management in Cloud Using Inclusive Power-Cognizant Processor Controller*. Ibtissam Sabbah: National Institute of Standards and Technology Special Publication. MINICT. (2017).

[23]. NIST cloud computing Reference Architecture. (2011). *NIST Special Publication 500-292.*

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar983

[24]. NIST. (n.d.). *NIST Cloud Computing Synopsis and Recommendation*. Retrieved from csrc.nist.gov: http://csrc.nist.gov/publications/drafts/800-146/Draft-NIST-SP800-146.pdf
[25]. (2021). *Open Data Center Alliance.* Information as a Service Rev. 1.0.
[26]. Punch, K. F. (2013). Introduction to Social Research. *Sage Publications*, 3rd ed.
[27]. R, K. C. (2004). *Research Methodology, 2nd Ed. New Delhi: New Age*. New Delhi: New Age Publisher.
[28]. Rajaan, T. &. (2020). *The use of the cloud increased dramatically.* OpenStack Foundation.
[29]. RDB. (2022). *data hosting facility for private and public sector entities.*
[30]. SEKARAN, U. (2009). A Skill-Building Approach. *Research Methods for Business*, 329.
[31]. *Sqrrl"s Take on the Big Data Ecosystem.* (2016, April 15). Retrieved from sqrrl.com: https://sqrrl.com/sqrrls-take-on-the-bigdata-ecosystem/
[32]. The Open Group, r. a. (2016, March 23). *www.opengroup.org/content.* Retrieved from opengroup: http://www.opengroup.org/content/reference-architecture-big-data- ecosystem
[33]. Turner, S. E. (2021). Strategies for Enhancing Small-Business Owners' Success Rates. *International Journal of Applied Management and Technology*, Vol.9 No.4.
[34]. Vaus, D. A. (2001). *Research Design in Social Research.* SAGE Publications. (2015). *World Economic Forum.* Global Index.