IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, January 2026
Impact Factor: 7.67

Ensuring Secure Decision Making: A Review of Data Warehouse Security in Business Intelligence Systems

[1]M Fatima, [2]S Krishnan, [3]K Nayanam
Department of Electrical and Electronics Engineering
ANSH Consultancy Pvt Ltd, Delhi
mfat01@gmail.com,snan40@gmail.com,knayanam@gmail.com

Abstract: *Business Intelligence (BI) is considered to have a high impact on businesses. Research activity has risen in the last years. An important part of BI systems is a well performing implementation of the Extract, Transform, and Load (ETL) process. In typical BI projects, implementing the ETL process can be the task with the greatest effort. Business Intelligence (BI) systems play a vital role in supporting organizational decision making by transforming large volumes of data into meaningful insights. At the core of these systems, data warehouses integrate data from multiple heterogeneous sources, making them critical assets for strategic, tactical, and operational decisions. However, the centralized, historical, and high-value nature of data warehouses also makes them attractive targets for security breaches, insider misuse, and privacy violations. Ensuring robust data warehouse security is therefore essential for maintaining the reliability and trustworthiness of BI-driven decision making. This review paper provides a comprehensive analysis of existing research on data warehouse security within the context of business intelligence systems. It examines key security requirements, including access control, authentication, encryption, inference control, auditing, data integrity, and privacy preservation, as discussed in the literature. The paper further reviews common security threats and vulnerabilities affecting data warehouses and analyzes proposed security frameworks, models, and best practices designed to mitigate these risks. By synthesizing findings from prior studies, this review highlights current challenges, research gaps, and emerging trends in securing data warehouses for effective decision support. The paper aims to serve as a reference for researchers and practitioners seeking to design secure, trustworthy, and resilient BI systems that support informed decision making*

Keywords: Business Intelligence, Data Warehouse, Decision Making , ETL, Operational Data, Metadata

I. INTRODUCTION

Business intelligence (BI) has gained wide recognition in the last years. It also got high business impact and is seen as a key enabler for increasing value and performance" [1]. Unsurprisingly, the progress of BI is monitored by management and IT consultants [2]. It is recognized as having a high relevance for the profit of businesses [3]. It is agreed that a strategic business intelligence approach will be needed [4]. At the same time, Business intelligence is a rather new discipline with a lot of research activity. Even though the term has been coined in 1958 [5], the number of published papers has risen considerably in the last few years. The rapid progress has also brought a high level of heterogeneity [6]; this causes both problems for businesses and offers research opportunities. It is possible to grasp the current state of BI and practitioner's literature tries to lay out a roadmap on how to implement BI in a company [7]. There is no reliable roadmap for BI progress, though. One important component of BI is the Extract, Transform and Load (ETL) process. It describes the gathering of data from various sources (extract), its modification to match a desired state (transformation) and its import into a database or data warehouse (load). ETL processes take up to 80% of the effort in BI projects [8]. A high performance is thereby vital to be able to process large amounts of data and to have a up-to-date database. The

ISSN: 2581-9429
Volume 6, Issue 3, January 2026
Impact Factor: 7.67

term ETL is known for a while [9] and the relevant market is already divided by a number of major players [10]. A data warehouse is predominantly used to store detailed summary data and metadata. Detailed data concern, for instance, sales or production volume in a given period. In order to increase effectiveness of queries, data in a data warehouse are subject to aggregation. Data e.g. on sales may be aggregated in a geographical dimension, a time period dimension or a product line dimension, etc. On the other hand, metadata include information on data themselves. They facilitate a process of extracting, transforming and loading data through presenting sources of data in the layout of data warehouses. Metadata are also used to automate summary data creation and queries management[11].

Furthermore, existing BI architectures typically feature a unidirectional communication flow between different components. The architectures proposed in [12] and [13] are good examples where they only feature a one-way data flow from data sources to data warehouse. The limitation of unidirectional data flow (i.e., no backward data flow from data warehouse to data sources) is that no adjustment or correction is allowed on data source even if an error is found. This may lead to the garbage-in-garbage out situation. If organizations want to correct the error, they have to repeat the entire BI process especially that of the cleansing procedures again. To overcome these problems, a two-way data integration flow [14] is suggested whereby the cleansed data can be sent back to data sources to improve accuracy and reduce cleansing work.

Another issue with existing BI architectures is the lack of support on metadata management. A good BI architecture should include the layer of metadata. A metadata repository is essential for business users to store and standardize metadata across different systems. By having a well-structured metadata, organizations will be able to track and monitor data flows within their BI environment [15]. In addition, they will be able to ensure the consistency of definitions and descriptions of data that support BI components and thus avoid misunderstanding and misinterpretation of data. Aside from that, some of the architectures do not include operational data store (ODS) within the BI environment. For instance, Watson's BI architecture (2009) [16] contains only data warehouse and data marts whereas [17] include only data warehouse. In order to address operational data needs of an organization, it is essential to implement ODS to provide current or near current integrated information that can be accessed or updated directly by users. Through this way, decision makers will be able to react faster to changing business environment and requirements. Furthermore, it is necessary to consider data staging area in the ETL (Extract Transform-Load) process. As most of the data from data source require cleansing and transformation, it is important to create a temporary storage for data to reside prior to loading into ODS or data warehouse. Without building this staging area, the process of working on the data [27]

II. BUSINESS INTELLIGENCE ARCHITECTURE

This paper describes a framework of a five layered BI architecture (see Figure 1), taking into consideration the value and quality of data as well as information flow in the system. The five layers are data source, ETL (Extract-Transform-Load), data warehouse, end user, and metadata layers. The rest of this section describes each of the layers[18].

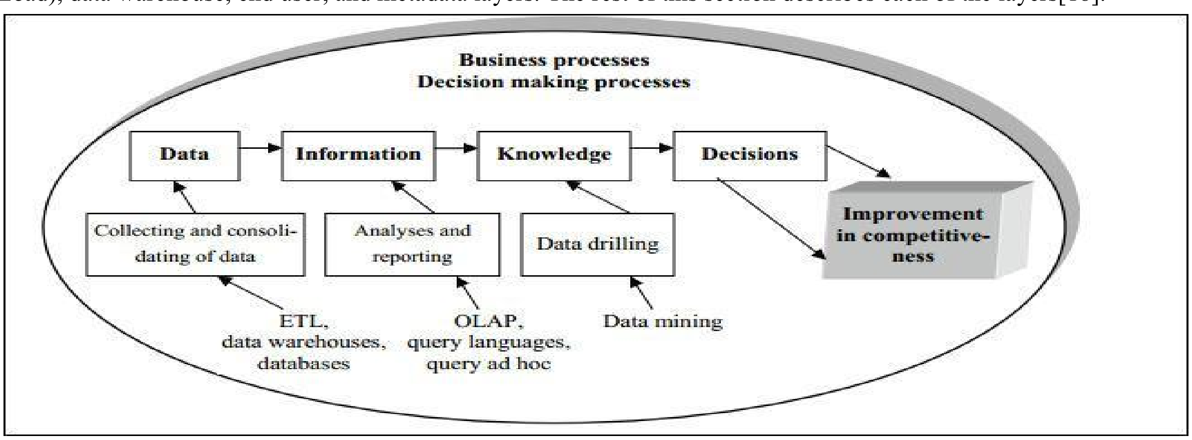

Figure 1: The role of BI systems in decision making

Data Source Layer

Nowadays, many application domains require the use of structured data as well as unstructured and semi-structured data to make effective and timely decision [12]. All these data can be acquired from two types of sources: internal and external.

Internal data source refers to data that is captured and maintained by operational systems inside an organization such as Customer Relationship Management and Enterprise Resource Planning systems. Internal data sources include the data related to business operations (i.e., customers, products, and sales data). These operational systems are also known as online transaction processing systems because they process large amount of transactions in real time and update data whenever it is needed. Operational systems contain only current data that is used to support daily business operations of an organization. Generally, operational 0mainly on specific business operations such as sales, accounting, and purchasing [19].External data source refers to those that originate outside an organization. This type of data can be collected from external sources such as business partners, syndicate data suppliers, the Internet, governments, and market research organizations [20]. These data are often related to competitors, market, environment (e.g., customer demographic and economic), and technology [21] .

It is important for organizations to clearly identify their data sources. Knowing where the required data can be obtained is useful in addressing specific business questions and requirements, thereby resulting in significant time savings and greater speed of information delivery.[44] Furthermore, the knowledge can also be used to facilitate data replication, data cleansing, and data extraction [26]

ETL (Extract-Transform-Load) Layer

This layer focuses on three main processes: Extraction, Transformation and Loading [17]. Extraction is the process of identifying and collecting relevant data from different sources Usually, the data collected from internal and external sources are not integrated, incomplete, and may be duplicated. Therefore, the extraction process is needed to select data that are significant in supporting organizational decision making. The extracted data are then sent to a temporary storage area called the data staging area prior to the transformation and cleansing process. This is done to avoid the need of extracting data again should any problem occurs. After that, the data will go through the transformation and the cleansing process.

Transformation is the process of converting data using a set of business rules (such as aggregation functions) into consistent formats for reporting and analysis. Data transformation process also includes defining business logic for data mapping and standardizing data definitions inorder to ensure consistency across an organization.

Data Warehouse Layer

There are three components in the data warehouse layer, namely operational data store, data warehouse, and data marts. Data flows from operational data store to data warehouse and subsequently to data

Operational Data Store

An operational data store (ODS) is used to integrate all data from the ETL layer and load them into data warehouses.

ODS is a database that stores subject-oriented, detailed, and current data from multiple sources to support tactical decision making It provides an integrated view of near real-time data such as transactions and prices. In addition, the data stored in ODS is volatile, which means it can be over-written or updated with new data that Blow into ODS [22]. As such, ODS does not store any historical data. Generally, ODS is designed to support operational processing and reporting needs of a specific application by providing an integrated view of data across many different business applications [23]. It is normally used by middle management level for daily management and short-term decision making [24]. Since the data stored in ODS are updated frequently (i.e., in minutes or hours), it is useful for reporting types that require real time (within 15 minutes) or near time (updated in 15 minutes to 1 hour) information [25]

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, January 2026
Impact Factor: 7.67

End User Layer

The end user layer consists of tools that display information in different formats to different users. These tools can be grouped hierarchically in a pyramid shape (as shown in Figure 2). As one moves from the bottom to the top of the pyramid, the degree of comprehensiveness at which data are being processed increases[12].

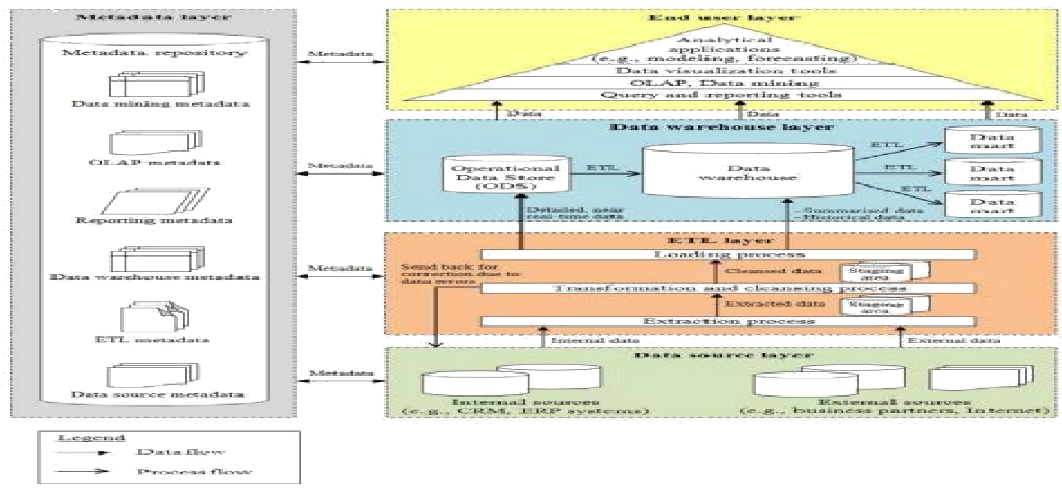

Fig 2: BI Architecture.

III. DATA WAREHOUSE SECURITY

Data warehouse security requires consistent management of sources, export tables, warehouse storage tables (conventional and cubes), and warehouse views. Warehouse permissions must meet data owners' requirements and be changed promptly if local concerns change. The system cannot need considerable administrator time because there are not sufficient individuals with technical abilities to comprehend derivation logic along with expertise in business to balance security and accessibility. To meet security needs and avoid costly adjustments, data warehouse security should be considered during design. [47,48]To determine security needs, legal, audit, network, and other factors must be examined[28].

Data migration involves moving data between storage types, formats, and computers. System installation, updating, and consolidation require it. Business needs have pushed many sectors to prioritize it. ETL is essential to data warehouse creation[29]. Multiple technologies are used to harvest data from various operations and load it into a data warehouse. This approach turns nonstandard data from many sources and operations into standard ones[30]. Systems and methods can assess a language structure in the raw information integration architecture to create logical syntax. Modern organizations rely more on Extract, Transform, and Load (ETL) and Data Warehousing solutions due to data-driven decisionmaking. Integrating, cleansing, and combining data from numerous sources into a single repository underpins analytical and business intelligence processes. Data volume and complexity raise the danger of unwanted access, data leakage, and system vulnerabilities. The authors in [31] covers ETL and Data Warehousing architecture, including essential stages, workflows, and technologies. Data breaches, insider threats, injection attacks, along with configuration issues that jeopardize data integrity and confidentiality are also examined.

3.1 Security Requirements and Challenges in Data Warehouses.

Data warehouses serve as the central repositories for business intelligence systems, integrating large volumes of historical and operational data from heterogeneous sources to support analytical processing and decision making. Due to their centralized architecture, long-term data retention, and strategic importance, data warehouses are particularly vulnerable to security threats[32]. Unauthorized access, data leakage, inference attacks, and insider misuse can

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, January 2026
Impact Factor: 7.67

significantly compromise the confidentiality, integrity, and availability of stored data, thereby undermining the reliability of BI-driven decisions. Consequently, ensuring robust security mechanisms within data warehouses is a critical requirement for organizations relying on data-driven decision making[33].

The security requirements of data warehouses extend beyond traditional database security due to their complex data integration processes and analytical workloads.[45,46] Key requirements include fine-grained access control to restrict data visibility based on user roles and privileges, strong authentication and authorization mechanisms, and encryption techniques to protect data both at rest and in transit. Additionally, inference control mechanisms are necessary to prevent users from deducing sensitive information through aggregate queries, which are common in analytical environments. Auditing and monitoring capabilities further play an essential role in detecting suspicious activities and ensuring accountability within data warehouse systems[34].

Despite extensive research, several challenges remain in implementing effective data warehouse security. The need to balance security with performance is a major concern, as security controls can introduce computational overhead and affect query response times. Furthermore, evolving regulatory requirements related to data protection and privacy, such as compliance with data governance frameworks, increase the complexity of securing data warehouses. As business intelligence systems increasingly incorporate cloud-based data warehouses and big data technologies, traditional security models must be adapted to address issues related to scalability, multi-tenancy, and dynamic access patterns. Addressing these challenges is essential to ensure that data warehouses continue to provide secure and trustworthy support for organizational decision making[35].Table 1 summarizes the key security aspects of data warehouses in business intelligence systems, highlighting their role in supporting secure and reliable decision making.

Table 1:Security aspects of Data warehouses in Business Intelligence Systems.

Security Aspect	Description	Purpose in Decision Making	Key Challenges
Access Control	Mechanism that restrivts user access based on roles, privilages and authorization levels.	Ensures that the decision makers only te relevant and permitted data.	Fine-grained policy enforcement.
Authentication	Verification of user identity before granting access to the data warehouse.	Prevents unauthorised usrsfrom influencing decision processes.	Credential management and insider threats.
Data Encryption	Protection of data at rest and in transit using cryptographic techniques.	Maintains confidentiality of sensitive analytical data.	Performance ovrhead and key management.
Inference Control	Techniques usd to prevent deduction of sensitive informationthrough aggregate queries.	Preserve privacy in analytical and reporting environments.	Query complexity and balancing usability with security.
Auditing and Monitoring	Logging and tracking of user activities	Enables accountability and detection of malicious behaviour	Storage overhead and real time analysis.
Data Integrity	Assurance that data remains accurate and consistent.	Ensures reliability and correctness of BI insights.	Data Integration error.
Privacy Preservation	Methods to rotect personal and sensitive data.	Builds trust and suport in Decision making.	.Regulatory compilance.
Availability	Ensuring continuous access to Data warehouse services.	Suports timely decision making.	Denial of Service attacks

3.2 Role of 5G/6G Networks in BI-Driven Decision Making.

The emergence of 5G and the anticipated evolution toward 6G networks have significantly transformed the data landscape by enabling ultra-low latency, massive connectivity, and high data throughput. These capabilities facilitate real-time and large-scale data collection from diverse sources such as Internet of Things (IoT) devices, smart infrastructure, and cyber–physical systems. Consequently, business intelligence systems increasingly rely on data warehouses to store, process, and analyze high-velocity and high-volume data streams generated over 5G and future 6G networks[36]. The integration of these advanced communication technologies enhances decision-making capabilities by supporting near real-time analytics, predictive modeling, and automated decision support.

However, the increased scale, heterogeneity, and velocity of data introduced by 5G and 6G networks also amplify security risks within data warehouses[37]. Network slicing, edge computing, and cloud-native architectures—key features of 5G and 6G—introduce new attack surfaces and complex trust boundaries. [44,45]As a result, ensuring secure data ingestion, storage, and analysis in data warehouses becomes a critical requirement for maintaining the integrity and reliability of BI-driven decisions in next-generation network environments.

3.3 Security Challenges for Data Warehouses in 5G/6G Environments.

In 5G- and 6G-enabled ecosystems, data warehouses must address security challenges that go beyond conventional enterprise settings. Massive machine-type communications generate continuous data flows that increase the risk of unauthorized access, data poisoning, and inference attacks[38]. Edge-based analytics, while reducing latency, complicate centralized security enforcement and auditing. Moreover, multi-tenancy and virtualization inherent in cloud-based data warehouses raise concerns related to data isolation, privacy preservation, and regulatory compliance. These challenges highlight the need for adaptive, scalable, and intelligence-driven security mechanisms capable of supporting secure decision making in future networked environments[39].Table 2 illustrates how the characteristics of 5G and emerging 6G networks directly influence data warehouse architectures and introduce new security requirements for business intelligence systems.[42,43] The massive device connectivity enabled by these networks leads to high-volume data ingestion, requiring scalable and secure storage mechanisms, while ultra-low latency communication supports near real-time analytics but demands robust, real-time access control[40]. The integration of edge and cloud computing distributes data processing across multiple layers, complicating centralized security enforcement and increasing the need for decentralized and coordinated protection mechanisms. Network slicing and virtualization create multi-tenant data environments that heighten concerns related to data isolation and fine-grained authorization. Furthermore, the AI-native nature of future 6G networks supports automated decision making but raises risks related to data poisoning and model integrity. Finally, increased cross-domain data sharing and mission-critical service requirements amplify the importance of privacy preservation, regulatory compliance, and high availability, highlighting the need for resilient data warehouse security frameworks to support reliable BI-driven decision making in next-generation network environments[41].

Table 2 Relationship Between Data Warehouse Security and 5G/6G-Enabled BI Systems

Aspect	5G/6G Characteristic	Impact on Data Warehouses	Security Implications
Data Volume	Massive device connectivity	High-volume data ingestion	Scalability and storage security
Data Velocity	Ultra-low latency communication	Near real-time analytics	Secure real-time access control
Network Architecture	Edge–cloud integration	Distributed data processing	Decentralized security enforcement
Network Slicing	Virtualized network segments	Multi-tenant data environments	Data isolation and access control

AI Integration	AI-native 6G networks	Automated BI decision support	Model integrity and data poisoning
Privacy Requirements	Cross-domain data sharing	Centralized analytical repositories	Privacy preservation and compliance
Availability	Mission-critical services	Continuous BI operations	Resilience against DoS attacks

IV. CONCLUSION

This paper has described a framework of five-layered BI architecture with various components. BI architecture plays an important role in affecting the success of a BI implementation. To have a smooth BI operation, organizations can benchmark their architectural plan against the framework proposed here. By having a good BI architecture, organizations will be able to maximize the value from their BI investments, and thereby meet their business requirements and improve business performance. However, at this point, the framework proposed in this paper remains conceptual in nature. Though it is built based on existing literature, the framework still needs to bevalidated using real-life BI cases to affirm its usability. Future research therefore can go along this line to validate the framework. This review examined the critical role of data warehouse security in enabling trustworthy business intelligence systems for effective decision making. By synthesizing existing literature, the paper highlighted key security requirements, threats, and protection mechanisms essential for safeguarding centralized analytical repositories. The review further emphasized how emerging 5G and future 6G networks, with their support for massive connectivity, ultra-low latency, and data-intensive applications, intensify both the opportunities and security challenges associated with data warehousing. As BI systems increasingly rely on real-time, distributed, and cloud-native data warehouses, traditional security approaches must evolve to address issues related to scalability, privacy, inference attacks, and multi-tenancy. The findings underscore the necessity of integrating adaptive, intelligence-driven security mechanisms into data warehouse architectures to ensure reliable and secure decision making in next-generation network environments. This paper provides a consolidated reference for researchers and practitioners and highlights future research directions toward resilient, privacy-preserving, and secure BI systems capable of supporting data-driven decisions in 5G- and 6G-enabled ecosystems.

REFERENCES

[1]. Watson, H. J., & Wixom, B. H. (2007). The current state of business intelligence. Computer, 40(9), 96-99.
[2]. Hagerty, J., Sallam, R. L., & Richardson, J. (2012). Magic quadrant for business intelligence platforms. Gartner for Business Leaders (February 6, 2012).
[3]. Sharma, V., & Joshi, S. (2018, June). A literature review on spectrum sensing in cognitive radio applications. In 2018 second international conference on intelligent computing and control systems (ICICCS) (pp. 883-893). IEEE. https://doi.org/10.1109/ICCONS.2018.8663089
[4]. Williams, S., & Williams, N. (2010). The profit impact of business intelligence. Elsevier.
[5]. Panian, Z. (2006, June). Business intelligence in support of business strategy. In Proceedings of the 7th WSEAS International Conference on Mathematics & Computers in Business & Economics (pp. 19-23).
[6]. Luhn, H. P. (1958). A business intelligence system. IBM Journal of research and development, 2(4), 314-319. https://doi.org/10.1147/rd.24.0314
[7]. Panian, Z. (2009, February). Expected progress in the field of business intelligence. In Proceedings of the 8th WSEAS international conference on Artificial intelligence, knowledge engineering and data bases (pp. 170-175).
[8]. Moss, L. T., &Atre, S. (2003). Business intelligence roadmap: the complete project lifecycle for decision-support applications. Addison-Wesley Professional.
[9]. Inmon, W. H. (2005). Building the data warehouse. John wiley& sons.

[10]. Kimball, R., Ross, M., Thornthwaite, W., Mundy, J., & Becker, B. (2008). The data warehouse lifecycle toolkit. John Wiley & Sons.

[11]. Sharma, V., Joshi, S. (2021). Real-Time Implementation of Enhanced Energy-Based Detection Technique. Proceedings of the International Conference on Paradigms of Computing, Communication and Data Sciences.

[12]. Da Silva, A. V. (2022). Implementing an SQL Based ETL Platform for Business Intelligence Solution (Master's thesis, Universidade NOVA de Lisboa (Portugal)).

[13]. Campante, M.I., Gonçalves, C.T., Gonçalves, M.J.A. (2024). Business Intelligence Tools to Improve Business Strategy. In: Carvalho, J.V., Abreu, A., Liberato, D., Rebolledo, J.A.D. (eds) Advances in Tourism, Technology and Systems. ICOTTS 2023. Smart Innovation, Systems and Technologies, vol 384. Springer, Singapore. https://doi.org/10.1007/978-981-99-9758-9_20

[14]. Baars, H., & Kemper, H. G. (2008). Management support with structured and unstructured data—an integrated business intelligence framework. Information systems management, 25(2), 132-148. https://doi.org/10.1080/10850530801941058

[15]. Shariat, M., & Hightower, R. (2007). Conceptualizing business intelligence architecture. Marketing Management Journal, 17(2), 40-46.V. Sharma and S. Joshi, "Design of Energy Detection based Multistage Sensing Technique," 2020 "Journal of Scientific Research "India , 2020, DOI:10.37398/JSR.2020.640255

[16]. Dayal, U., Castellanos, M., Simitsis, A., & Wilkinson, K. (2009, March). Data integration flows for business intelligence. In Proceedings of the 12th International Conference on Extending Database Technology: Advances in Database Technology (pp. 1-11). https://doi.org/10.1145/1516360.1516362

[17]. Pant, P. (2009). Essential Components of a Successful BI Strategy. Information Management.

[18]. Watson, H. J. (2009). Tutorial: business intelligence–past, present, and future. Communications of the Association for Information systems, 25(1), 39.

[19]. Sen, A., &Sinha, A. P. (2005). A comparison of data warehousing methodologies. Communications of the ACM, 48(3), 79-84.

[20]. Sharma, Vatsala, and Kamal Nayanam, "A survey on Smart Railway Track Fault Detection Using IOT", IOSR Journal of Engineering 11 (08), pp. 38-42, 2021

[21]. Olszak, C. M., &Ziemba, E. (2004). Business intelligence systems as a new generation of decision support systems. In Proceedings of PISTA 2004, International Conference on Politics and Information Systems: Technologies and Applications.

[22]. Alshikhi, O. A., & Abdullah, B. M. (2018). Information quality: definitions, measurement, dimensions, and relationship with decision making. European Journal of Business and Innovation Research, 6(5), 36-42.

[23]. Ranjan, J. (2009). Business intelligence: Concepts, components, techniques and benefits. Journal of theoretical and applied information technology, 9(1), 60-70.

[24]. Haag, S., Cummings, M., & Dawkins, J. (1999). Management information systems for the information age. McGraw-Hill Higher Education.

[25]. Imhoff, C., Galemmo, N., & Geiger, J. G. (2003). Mastering data warehouse design: relational and dimensional techniques. John Wiley & Sons.

[26]. S Shivam, P Raj, V Sharma "A Survey Non-Terrestrial Networks in 6G/ 7G Smart Network for 2035+ and Beyond " International Journal of Advanced Research in Science, Communication and Technology, Volume 5, Issue 5, December 2025. ISSN: 2581-9429.

[27]. Chan, J. O. (2005). Optimizing data warehousing startegies. Communications of the IIMA, 5(1), 1.

[28]. Li, Z., Huang, Y., Wan, S. (2007). Model Analysis of Data Integration of Enterprises and E-Commerce Based on ODS. In: Xu, L.D., Tjoa, A.M., Chaudhry, S.S. (eds) Research and Practical Issues of Enterprise Information Systems II. IFIP — The International Federation for Information Processing, vol 254. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-75902-9_28

[29]. AAnand, Shalu, R Bharti, A Mishra, A Kumar V Sharma "IOT Based Home Security Smart System Using Arduino" International Journal of Advance Research, Ideas and Innovations in Technology, 2023; 10: I1 - V10I1-1184. https://www.ijariit.com.

[30]. Boulahia, C., Behja, H., ChbihiLouhdi, M.R. et al. The multi-criteria evaluation of research efforts based on ETL software: from business intelligence approach to big data and semantic approaches. Evol. Intel. 17, 2099–2124 (2024). https://doi.org/10.1007/s12065-023-00899-z

[31]. Agarwal, S., Singh, A. P., &Anand, N. (2013, July). Evaluation performance study of Firefly algorithm, particle swarm optimization and artificial bee colony algorithm for non-linear mathematical optimization functions. In 2013 fourth international conference on computing, communications and networking technologies (ICCCNT) (pp. 1-8). IEEE. https://doi.org/10.1109/ICCCNT.2013.6726474

[32]. Anand, N., & Kumar, M. (2013, July). Modeling and optimization of extraction-transformation-loading (ETL) processes in data warehouse: An overview. In 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT) (pp. 1-5). IEEE.https://doi.org/10.1109/ICCCNT.2013.6726592

[33]. Anand, N., & Sharma, P. (2014). Data Warehouse Security through Conceptual Models.

[34]. Anand, N. (2014). ETL and its impact on Business Intelligence. International Journal of Scientific and Research Publications, 4(2), 1.

[35]. Anand, N., & Kumar, M. (2013, June). An Overview on Data Quality Issues at Data Staging ETL. In Proceedings of the International Conference on Advances in Computer Science and Application, Lucknow, India (pp. 21-22).

[36]. Vatsala Sharma, “Optimization of Performance of Cooperative Spectrum Sensing in Mobile Cognitive Radio Networks,” Journal of Emerging Technologies and Innovative Research, vol. 10, no. 4, pp. b579-b583, 2023.

[37]. NitinAnand, Vatsala Sharma, Pardeep Singh (2025); ETL and Data Warehousing: Architecture, Vulnerabilities, and Security Mechanisms; International Journal of Scientific and Research Publications (IJSRP) 15(10) (ISSN: 2250-3153), DOI: http://dx.doi.org/10.29322/IJSRP.15.10.2025.p16612

[38]. Anand, P. S. N. (2014). Framework for The Integrated And Validated Model of Data Warehouse. American Journal of Engineering Research (AJER), e-ISSN, 2320-0847.

[39]. Anand, N., Singh, K.J. (2024). A Comprehensive Study of DDoS Attack on Internet of Things Network. In: Swain, B.P., Dixit, U.S. (eds) Recent Advances in Electrical and Electronic Engineering. ICSTE 2023. Lecture Notes in Electrical Engineering, vol 1071. Springer, Singapore. https://doi.org/10.1007/978-981-99-4713-3_56

[40]. Anand, N., Singh, K.J. (2023). An Overview on Security and Privacy Concerns in IoT-Based Smart Environments. In: Rao, U.P., Alazab, M., Gohil, B.N., Chelliah, P.R. (eds) Security, Privacy and Data Analytics. ISPDA 2022. Lecture Notes in Electrical Engineering, vol 1049. Springer, Singapore. https://doi.org/10.1007/978-981-99-3569-7_21

[41]. N. Anand, P. Raj, S. Shivam and V. Sharma, "A Layer based Aspect of the Security Issues in Internet of Things: An Analytical Survey," 2025 International Conference on Intelligent and Secure Engineering Solutions (CISES), Greater Noida GautamBudh Nagar, India, 2025, pp. 34-40, https://doi.org/10.1109/CISES66934.2025.11265603

[42]. Kumar, M., Lal, I.B., Ranjan, R., Kumar, N., Kumar, N., Anand, N. (2025). Optimizing Modulation Schemes for 5G Efficiency Networks. In: Ghonge, M.M., Liu, H., Khan, M., Tran, T.A. (eds) Advances in Emerging Technologies and Computing Innovations. ICETCI 2025. Sustainable Artificial Intelligence-Powered Applications. Springer, Cham. https://doi.org/10.1007/978-3-031-92854-3_39

[43]. Sharma, V., &Nayanam, K. (2024). Sixth Generation (6G) to the Waying Seventh (7G) Wireless Communication Visions and Standards, Challenges, Applications. Int. J. Adv. Res. Sci. Technol, 13, 1248-1255.

[44]. Nayanam, K., Gandhi, R., &Vishwavidyalaya, P. (2024). Cognitive radio based enhanced compressive spectrum sensing technique for 5G adhoc networks. Int. J. Eng. Res, 10.

[45]. Vishwakarma, R., Jain, A.K. A survey of DDoS attacking techniques and defence mechanisms in the IoT network. TelecommunSyst 73, 3–25 (2020). https://doi.org/10.1007/s11235-019-00599-z

ISSN: 2581-9429
Volume 6, Issue 3, January 2026
Impact Factor: 7.67

[46]. R. Vishwakarma and A. K. Jain, "A Honeypot with Machine Learning based Detection Framework for defending IoT based Botnet DDoS Attacks," 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019, pp. 1019-1024, https://doi.org/10.1109/ICOEI.2019.8862720

[47]. Sharma, V., Joshi, S. (2021). Design of Hybrid Blind Detection Based Spectrum Sensing Technique. Journal of Scientific Research, 2020, Vol 12, Issue 4, p575. Academic Journal. https://doi.org/10.3329/jsr.v12i4.46870.

[48]. Nayanam K. and Sharma V., "TOWARDS ARCHITECTING RESEARCH PERSPECTIVE FUTURE SCOPE WITH CHAT GPT," Jul. 2024.

DOI: 10.48175/IJARSCT-30946