Applicability of Generative Semantic Communications to Satellite Networks

Hyein Lee*, Sooyoung Kim*, Heewook Kim†, Jihong Park‡, Jinho Choi§, Daesub Oh†
* IT Convergence Research Center, Division of EE, Jeonbuk National University, Jeonju, Korea
† Radio & Satellite Research Division, ETRI, Daejeon, Korea
‡ Information Systems Technology and Design Pillar, Singapore University of Technology, 487372 Singapore
§ School of Electrical and Mechanical Engineering, The University of Adelaide, Adelaide, SA 5005, Australia
Emails: {leehyein96, sookim}@jbnu.ac.kr, {prince304, trap}@etri.re.kr, jihong_park@sutd.edu.sg, jinho.choi@adelaide.edu.au

***Abstract*—This paper explores the applicability of generative semantic communications (GSC) in satellite networks. By integrating semantic compression with generative artificial intelligence, GSC enables efficient downlink transmission by allowing users to reconstruct content from compact semantic prompts. Given the limited and costly power and bandwidth resources in satellite systems, GSC offers significant potential for improved resource utilization, thereby enhancing overall capacity. The paper presents how GSC can be implemented in satellite networks and highlights several use cases where it offers distinct advantages. Furthermore, key challenges associated with the adoption of GSC in satellite communication environments are discussed.**

***Index Terms*—semantic communications, generative model, satellite networks**

I. Introduction

Generative semantic communications (GSC) represents a transformative approach to data transmission, focusing on conveying only the most semantically meaningful information while minimizing data volume. Instead of transmitting raw data, GSC sends concise prompts or tokens containing essential semantic features, which receivers can use to reconstruct contextually equivalent information by using generative artificial intelligence (AI). This framework significantly reduces bandwidth consumption, lowers energy requirements, and improves latency, making it particularly advantageous in resource-constrained environments like satellite networks.

Prior studies have examined diverse system designs that integrate generative models into communication. One line of work has explored downlink frameworks where text-to-image generators allow generative users to reconstruct images from textual prompts, while non-generative users receive the original data, thereby reducing transmission energy at the expense of local computation [1]. Moving beyond such task-specific designs, broader frameworks have been proposed that integrate generative AI into semantic communication over cloud–edge–mobile architectures, supporting multimodal provisioning, joint source–channel coding, and semantic calibration through the cooperation of global and local models [2]. Further, GSC has been extended to immersive applications through semantic-aware extended reality (XR) frameworks, where generative AI enhances semantic communication to deliver multimodal and context-rich content [3].

Building on these developments, recent efforts have begun to investigate GSC in satellite communications. In this context, scarce spectrum resources, long propagation delays, and frequent attenuation events make semantic compression particularly appealing. To address these challenges, adaptive encoder–decoder mechanisms have been proposed to preserve critical semantic features, while reference images are leveraged to repair those degraded by sudden channel attenuation. Moreover, lightweight error detection at regenerative satellites enables early identification of semantic distortion without relying on costly retransmissions across long-delay links [4].

At a broader scale, recent work has focused on mega-constellation LEO satellite networks, investigating GSC from a system and networking perspective. In these studies, generative AI is leveraged not only to reconstruct semantic content from compact prompts but also to support architectural designs that address spectrum scarcity, latency constraints, and multimedia-rich traffic. Using temporal graph-based models, semantic encoder–decoder deployment strategies, and GSC-aware routing schemes, this line of research demonstrates how GSC can be scaled to next-generation non-terrestrial networks [5].

Extending beyond satellite-focused studies, further research has examined the application of GSC in non-terrestrial network architectures. In these settings, generative AI serves as a unifying enabler for semantic-aware communication across heterogeneous layers, addressing challenges such as dynamic topology, multimodal content delivery, and resource heterogeneity. These works emphasize that while satellite networks provide an essential foundation, expanding GSC to encompass integrated architectures offers a more comprehensive path toward resilient and intelligent communication systems [6].

While these studies provide important theoretical insights and outline promising design directions, they often fall short in presenting practical scenarios that demonstrate how such frameworks could be applied in real satellite communication

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2021-0-00719, Development of the spectrum sharing technology for Non-GSO satellite system) and under the framework of international cooperation program managed by National Research Foundation of Korea (No. RS-2024-00459799).

environments. Motivated by these gaps, this paper emphasizes practical applicability by examining concrete use cases of GSC in satellite networks and outlining key challenges that must be addressed for its realization. The remainder of this paper is organized as follows. Section II presents various use cases of GSC in satellite networks, highlighting their potential benefits. Section III discusses the key challenges for practical adoption and future research directions. Finally, Section IV concludes the paper.

II. Use-Cases of Generative Semantic Communications for Satellite Systems

Figure 1 illustrates the configuration of downlink communications and the application of GSC across various satellite network-enabled scenarios. Unlike traditional communication systems that assume all users require full data transmission, GSC introduces a newparadigm where users can use their ability to locally generate content [1]. This foundational concept serves as the basis for a range of application specific use cases, which are discussed in the following subsections.

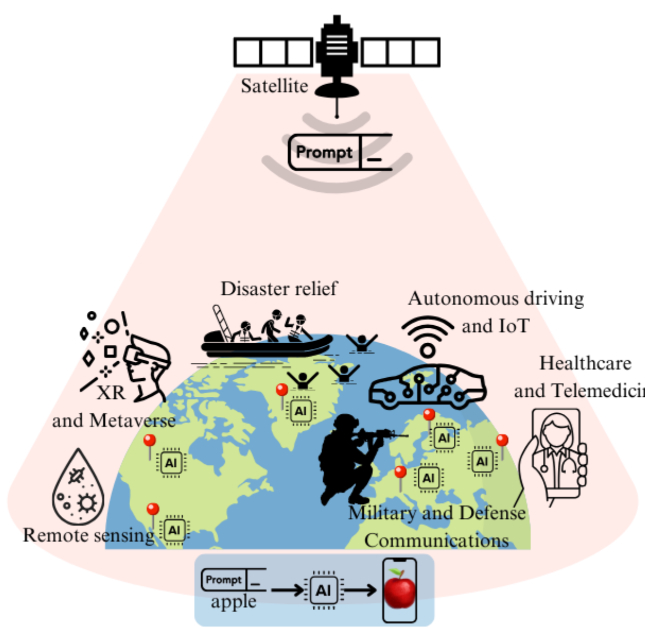

Fig. 1: An illustration of downlink communications and possible use cases for GSC with satellite network

In the GSC scenario, users are classified into two categories: traditional users who require full data transmission, and users who can leverage their intelligent capabilities to locally generate content. These are referred to as off-loading users (OUs) and generative users (GUs), respectively. As illustrated in Fig. 1, the transmitted prompt, for example, the word "apple", is interpreted by the GU's on-device generative AI model to produce a visual representation corresponding to the intended content. In this framework, the prompt functions as a highly compressed semantic abstraction, while the generative model at the user terminal reconstructs the associated output without necessitating transmission of the full-resolution image. This represents only one example of GSC in practice and is not limited to text-to-image generation. More broadly, the concept encompasses any scenario where the input prompt semantically encapsulates the core information of the target output. For instance, a single image could serve as a prompt for generating a corresponding video sequence using image-to-video generation models, or a short audio cue might lead to the reconstruction of a full voice message.

A. Disaster relief use case for satellite system

In large-scale disasters such as earthquakes, floods, or hurricanes, terrestrial communication infrastructures often become inoperable, leaving affected regions isolated. Satellite networks provide crucial connectivity in such scenarios, but the transmission of high-resolution imagery or continuous video streams from disaster zones can overwhelm the limited bandwidth and power resources available in satellite communications.

GSC addresses this challenge by focusing on transmitting only the most semantically meaningful information extracted from raw data. For instance, rather than sending a full-resolution video showing rescue operations, GSC can distill this into text-based prompts containing essential information such as the location of stranded individuals, estimated damage levels, and resource needs. Upon receiving these prompts, ground stations or response teams can utilize GenAI models—such as GANs—to reconstruct detailed situational maps that closely resemble the original satellite images [7], [8].

B. Remote sensing use case

Remote sensing applications, such as climate monitoring, deforestation tracking, and ocean surveillance, generate vast amounts of data that require efficient transmission for timely analysis [9]. GSC can optimize remote sensing by transmitting only the essential environmental features required for analysis. For example, in scenarios like ocean surveillance, GSC can distill vast datasets into key indicators such as chlorophyll levels or algal bloom patterns. Instead of transmitting entire oceanographic images, satellites send summarized environmental data allowing for the reconstruction of ocean health maps without overwhelming data transfer channels. This ensures timely environmental assessments and facilitates proactive responses to ecological changes.

A recent work in SC for remote sensing shows that attention-based feature selection and joint source–channel coding can achieve extremely high compression ratios—up to 384×—while preserving key scene-level information even in noisy channel conditions [10]. By extracting only the most relevant semantic features for tasks (e.g., classification or scene recognition), this method aligns well with the GSC principle of sending "meaning-centric" data, thus enabling robust, bandwidth-efficient transmission of large-scale satellite imagery.

C. Military and defense use case for satellite communications

Military operations demand secure, reliable, and efficient communication networks. The need for real-time data transmission including command instructions, reconnaissance images, and situational updates often exceeds the capacity of traditional communication systems. Satellite networks can strongly support military and defense communications especially in remote battlefields where terrestrial infrastructure is unavailable or compromised.

For instance, in battlefield scenarios, soldiers equipped with augmented reality (AR) displays such as military smart goggles can benefit from GSC by receiving only the most essential data. GSC transmits minimal yet critical information which AI systems on the AR devices can quickly reconstruct into detailed tactical maps. Similarly, military drones (e.g., UAVs) can utilize GSC to summarize key reconnaissance information such as enemy movement paths and identification details. Instead of transmitting full video streams of enemy tank movements, GSC can send concise messages like "Five tanks moving northwest, 10 km from the current position." By reducing the volume of transmitted data and focusing on essential information, GSC can accelerate swift real-time decision-making but also minimizes the risk of data interception contributing to advanced secure and resilient defense operations.

Furthermore, GSC offers a strategic advantage by enabling the transmission of encrypted, semantically compressed data ensuring that only mission-critical information is communicated. In high-risk scenarios where data security is critical, the security of GSC can be further strengthened by integrating secure technologies [11]–[13]. Specifically, it has been demonstrated that homomorphic encryption is capable of preserving semantic features within encrypted data [14], and deep neural network based secured SC method can improve reliability and security through two phase training process [15].

D. Satellite-based autonomous driving and IoT use cases

Autonomous vehicles (AVs) and intelligent transportation systems depend on robust, real-time communication networks to ensure safety, efficiency, and reliability. In urban environments, terrestrial networks often support these communications; however, in rural, remote, or underdeveloped regions, terrestrial infrastructure may be insufficient or unavailable. Satellite networks provide an essential backbone for beyond-line-of-sight connectivity, enabling consistent and reliable communication for AVs in areas lacking traditional network coverage. This satellite-based communication is crucial for ensuring seamless vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) interactions, even in challenging environments.

GSC can significantly optimize V2V and V2I communication by transmitting only the most relevant semantic information instead of raw sensor or video data. For example, rather than sharing entire camera feeds between vehicles to prevent collisions, GSC can distill this data into key metrics such as vehicle speed, lane change status, and potential collision risks. This reduction in transmitted data minimizes bandwidth consumption and improves the response time for real-time safety applications [16]–[18]. Similarly, in smart traffic management systems, GSC can be applied to optimize data transmission from urban surveillance systems like CCTV. Instead of transmitting full-resolution video feeds to traffic control centers, GSC can summarize critical data such as traffic density, congestion patterns, and pollution level [19].

E. XR and metaverse use case for satellite communications

XR and metaverse applications demand high bandwidth and low latency for immersive, real-time experiences. Transmitting large volumes of 3D graphics, environmental data, and user interactions over satellite networks poses significant challenges [20]–[22]. SC addresses these challenges by transmitting only high-level semantic representations of virtual environments instead of raw graphical data. Rather than delivering complete 3D models or texture files, the system encodes essential scene attributes such as object positions, spatial relationships, and contextual metadata—and transmits them efficiently. At the user terminal, GenAI models reconstruct full 3D scenes and interactions based on these compact semantic cues, significantly reducing the required bandwidth. This semantic-driven reconstruction enables scalable, real-time XR delivery even in constrained satellite communication environments.

Without GSC, XR and metaverse applications would require the transmission of full 3D models and high-resolution textures, resulting in excessive bandwidth usage and increased latency. For example, in remote virtual training simulations for military or industrial applications, GSC prioritizes the transmission of essential 3D models and interaction data, reducing latency and enhancing user experience. This approach ensures that even in bandwidth-limited environments, high-quality XR experiences can be delivered.

F. Satellite-based healthcare and telemedicine use case

Telemedicine and remote healthcare services rely heavily on high-quality data transmission, particularly for diagnostic imaging and real-time consultations. In remote areas with limited access to medical facilities or during emergencies where terrestrial networks are unavailable, satellite communication plays a critical role in maintaining healthcare connectivity [23], [24]. In such scenarios, GSC can significantly enhance the efficiency and responsiveness of telemedicine. Rather than transmitting full medical datasets—such as complete magnetic resonance imaging (MRI) or computed tomography (CT) scans—GSC enables the delivery of only essential diagnostic information. For example, compressed semantic prompts generated by AI can highlight key regions of interest, allowing healthcare providers to make timely decisions based on minimal but meaningful data. This reduces bandwidth consumption and avoids delays associated with transferring large volumes of medical data.

Moreover, the integration of federated learning into this framework supports privacy-preserving remote diagnostics by allowing AI models to be trained and deployed locally at user terminals without sharing raw patient data. This combination of GSC and federated learning offers a scalable and secure solution for delivering effective healthcare services [25], [26].

III. Challenges and Future Works

While GSC-enabled satellite systems are expected to offer promising gains in resource efficiency, several challenges must be addressed to fully realize their potential in next-generation satellite networks. First, reconstruction errors induced by semantic compression need careful attention. Although current frameworks often assume that semantic compression preserves the fidelity of reconstructed content, the quality of data generated by GenAI may degrade as the compression ratio increases. However, a key limitation in current research is the absence of a well-defined and universally accepted metric for quantifying reconstruction accuracy. This lack of formal definition makes it difficult to objectively evaluate the quality of the generated content, and consequently, many existing studies have not systematically explored the fundamental trade-off between transmission efficiency and the fidelity of reconstructed data.

Second, the heterogeneous nature of GUs must be carefully considered when designing GSC-enabled satellite systems. In real-world scenarios, user terminals can vary significantly in their computational capabilities, access to memory and storage, and support for on-device generative models. Furthermore, users may differ in their application requirements, including latency sensitivity, quality-of-service expectations, and service-level agreements. This variability implies that a one-size-fits-all approach to semantic reconstruction may be suboptimal. Therefore, extending the GSC framework to include differentiated service models—such as assigning priority weights, quality grades, or adaptive semantic fidelity levels to individual GUs—could enable more efficient and user-aware RA strategies.

Third, integrating GSC into existing RA mechanisms introduces additional layers of complexity. Traditional RA schemes in satellite networks often rely on either analytically derived optimization frameworks or data-driven approaches based on machine learning. These methods typically focus on physical- or network-layer parameters such as channel condition, the system bandwidth, frequency reuse factor, and antenna capability. However, incorporating semantic-level constraints and performance metrics into the RA process significantly expands the solution space. This semantic dimension introduces new interdependencies between compression, content reconstruction, and network behavior, which may not be easily captured by conventional models. As a result, novel RA frameworks that jointly optimize across physical, network, and semantic layers may be required, potentially increasing computational burden and system design complexity.

Fourth, real-world satellite networks are characterized by time-varying and distributed environments, which present fundamental challenges to the scalability and robustness of GSC frameworks. Factors such as orbital dynamics, handovers between satellites, varying propagation delays, and intermittent connectivity can disrupt semantic continuity and complicate model synchronization between satellite and ground segments. In addition, the presence of multi-satellite constellations and inter-satellite links introduces coordination requirements that are not trivial to address. Designing GSC systems that can adapt to these dynamic topologies while maintaining consistent semantic performance will require flexible protocols, robust synchronization strategies, and scalable model management techniques.

Finally, although semantic compression inherently obscures transmitted content by focusing on meaning rather than raw data, the integration of generative AI components introduces new vulnerabilities related to trust, privacy, and security. For instance, adversarial attacks targeting generative models could result in the synthesis of misleading or harmful outputs. Moreover, untrusted generative models may unintentionally leak sensitive information through latent representations or prompt reversals. Therefore, future research should explore the development of secure GSC architectures that combine privacy-preserving semantic compression, verifiable and trustworthy generative models, and physical-layer security techniques. This would ensure that semantic communications in satellite networks remain both efficient and resilient against emerging security threats.

IV. Conclusion

In this paper, we have explored a range of important use cases for GSC-enabled satellite networks, including disaster relief and other mission-critical applications, with a particular focus on the benefits of GSC from a resource utilization perspective. By leveraging semantic compression and generative reconstruction, GSC has the potential to significantly enhance the efficiency of downlink transmissions, thereby enabling more effective use of the limited and costly power and bandwidth resources in satellite systems. Despite these advantages, several challenges must still be addressed before GSC can be fully realized in practical satellite networks. These include increased computational complexity, heterogeneous user capabilities, adaptation to dynamic network topologies, and emerging security concerns related to generative AI components. Nonetheless, the analysis clearly indicates that GSC offers a promising path toward substantial capacity enhancements in satellite communications, primarily by enabling more intelligent and efficient allocation of satellite resources. Continued research and development in this area will be essential to unlock the full potential of GSC in next-generation satellite systems.

References

[1] H. Lee, J. Park, S. Kim, and J. Choi, "Energy-Efficient Downlink Semantic Generative Communication with Text-to-Image Generators," in *2023 IEEE Globecom Workshops (GC Wkshps)*, 2023, pp. 1291–1296.

[2] L. Xia, Y. Sun, C. Liang, L. Zhang, M. A. Imran, and D. Niyato, "Generative AI for Semantic Communication: Architecture, Challenges, and Outlook," *IEEE Wireless Communications*, vol. 32, no. 1, pp. 132–140, 2025.

[3] W. Yang, Z. Xiong, T. Q. S. Quek, and X. Shen, "Streamlined Transmission: A Semantic-Aware XR Deployment Framework Enhanced By Generative AI," *IEEE Network*, vol. 38, no. 6, pp. 29–38, 2024.

[4] P. Jiang, C.-K. Wen, X. Li, S. Jin, and G. Y. Li, "Semantic Satellite Communications Based on Generative Foundation Model," *IEEE Journal on Selected Areas in Communications*, vol. 43, no. 7, pp. 2431–2445, 2025.

[5] G. Binquan, Y. Wanting, X. Zehui, Z. Zhou, L. Baosheng, H. Zhu, T. Rahim, and T. Q. S. Quek, "Enhancing Mega-Satellite Networks with Generative Semantic Communication: A Networking Perspective," 2025. [Online]. Available: https://arxiv.org/abs/2508.07573

[6] R. Zhang, H. Du, D. Niyato, J. Kang, Z. Xiong, A. Jamalipour, P. Zhang, and D. I. Kim, "Generative AI for Space-Air-Ground Integrated Networks," *IEEE Wireless Communications*, vol. 31, no. 6, pp. 10–20, 2024.

[7] G. Raja, A. Manoharan, and H. Siljak, "Ugen: Uav and GAN-aided Ensemble Network for Post-Disaster Survivor Detection Through Oran," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 7, pp. 9296–9305, 2024.

[8] X. Rui, Y. Cao, X. Yuan, Y. Kang, and W. Song, "DisasterGAN: Generative Adversarial Networks for Remote Sensing Disaster Image Generation," *Remote Sensing*, vol. 13, no. 21, 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/21/4284

[9] O. Dubovik, G. L. Schuster, F. Xu, Y. Hu, H. Bösch, J. Landgraf, and Z. Li, "Grand Challenges in Satellite Remote Sensing," p. 619818, 2021.

[10] Y. Jiang, K. Xie, Y. Ouyang, J. Wen, G. Zhang, W. Liang, and Q. Feng, "High Quality Compression and Transmission of Remote Sensing Images Based on Semantic Communication," *IEEE Transactions on Sustainable Computing*, pp. 1–15, 2025.

[11] C. Zhao, H. Du, D. Niyato, J. Kang, Z. Xiong, D. I. Kim, X. Shen, and K. B. Letaief, "Generative AI for Secure Physical Layer Communications: A Survey," *IEEE Transactions on Cognitive Communications and Networking*, vol. 11, no. 1, pp. 3–26, 2025.

[12] M. Shen, J. Wang, H. Du, D. Niyato, X. Tang, J. Kang, Y. Ding, and L. Zhu, "Secure Semantic Communications: Challenges, Approaches, and Opportunities," *IEEE Network*, vol. 38, no. 4, pp. 197–206, 2024.

[13] S. Guo, Y. Wang, N. Zhang, Z. Su, T. H. Luan, Z. Tian, and X. Shen, "A Survey on Semantic Communication Networks: Architecture, Security, and Privacy," *IEEE Communications Surveys Tutorials*, pp. 1–1, 2024.

[14] R. Meng, D. Fan, H. Gao, Y. Yuan, B. Wang, X. Xu, M. Sun, C. Dong, X. Tao, P. Zhang, and D. Niyato, "Secure Semantic Communication with Homomorphic Encryption," 2025. [Online]. Available: https://arxiv.org/abs/2501.10182

[15] Y. Li, Z. Shi, H. Hu, Y. Fu, H. Wang, and H. Lei, "Secure Semantic Communications: From Perspective of Physical Layer Security," *IEEE Communications Letters*, vol. 28, no. 10, pp. 2243–2247, 2024.

[16] J. Lu, W. Yang, Z. Xiong, C. Xing, R. Tafazolli, T. Q. S. Quek, and M. Debbah, "Generative AI-Enhanced Multi-Modal Semantic Communication in Internet of Vehicles: System Design and Methodologies," 2024. [Online]. Available: https://arxiv.org/abs/2409.15642

[17] R. Zhang, K. Xiong, H. Du, D. Niyato, J. Kang, X. Shen, and H. V. Poor, "Generative AI-Enabled Vehicular Networks: Fundamentals, Framework, and Case Study," *IEEE Network*, vol. 38, no. 4, pp. 259–267, 2024.

[18] A. D. Raha, M. S. Munir, A. Adhikary, Y. Qiao, and C. S. Hong, "Generative AI-Driven Semantic Communication Framework for Nextg Wireless Network," 2023. [Online]. Available: https://arxiv.org/abs/2310.09021

[19] N. Zhang, H. Chen, X. Chen, and J. Chen, "Semantic Framework of Internet of Things for Smart Cities: Case Studies," *Sensors*, vol. 16, no. 9, 2016. [Online]. Available: https://www.mdpi.com/1424-8220/16/9/1501

[20] B. Zhang, Z. Qin, Y. Guo, and G. Y. Li, "Semantic Sensing and Communications for Ultimate Extended Reality," 2022. [Online]. Available: https://arxiv.org/abs/2212.08533

[21] S. K. Jagatheesaperumal, Z. Yang, Q. Yang, C. Huang, W. Xu, M. Shikh-Bahaei, and Z. Zhang, "Semantic-Aware Digital Twin for Metaverse: A Comprehensive Review," *IEEE Wireless Communications*, vol. 30, no. 4, pp. 38–46, 2023.

[22] M. Z. Aloudat, A. Aboumadi, A. Soliman, H. A. Al-Mohammed, M. Al-Ali, A. Mahgoub, M. Barhamgi, and E. Yaacoub, "Metaverse Unbound: A Survey on Synergistic Integration Between Semantic Communication, 6G, and Edge Learning," *IEEE Access*, vol. 13, pp. 58 302–58 350, 2025.

[23] A. Athama, K. Wang, X. Chen, and Y. Li, "Semantic Communications for Healthcare Applications: Opportunities and Challenges," in *2024 IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT)*, 2024, pp. 383–388.

[24] W. Xiao, Y. Tang, J. Liu, D. Wu, B. Alzahrani, Y. Hao, and N. Zhou, "Semantic-Driven Efficient Service Network Towards Smart Healthcare System in Intelligent Fabric," *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 5, pp. 2480–2489, 2023.

[25] J. Li, Y. Meng, L. Ma, S. Du, H. Zhu, Q. Pei, and X. Shen, "A Federated Learning Based Privacy-Preserving Smart Healthcare System," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 3, pp. 2021–2031, 2022.

[26] A. K. Bashir, N. Victor, S. Bhattacharya, T. Huynh-The, R. Chengoden, G. Yenduri, P. K. R. Maddikunta, Q.-V. Pham, T. R. Gadekallu, and M. Liyanage, "Federated Learning for the Healthcare Metaverse: Concepts, Applications, Challenges, and Future Directions," *IEEE Internet of Things Journal*, vol. 10, no. 24, pp. 21 873–21 891, 2023.