Grenze International Journal of Engineering and Technology, June Issue

Artificial Intelligence Techniques for 6G Network Communication: A Comprehensive Review and Performance Analysis

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***Abstract*— Exponential development in the volume of associated wireless equipment such as telephones, energy-efficient Internet of Things (IoT) products, connected automobiles, etc. will enhance the size of the forthcoming generations wireless networks i.e. 5G advanced, and 6G. Moreover, expected use cases include linked self-driven automobiles, robots, drones, smart residences and urban areas, wireless connectivity of commercial infrastructure, and holographic transmission for 6G networks will require minimal latency and exceptionally high accuracy. Conventional and standard techniques are not appropriate for the efficiency, coordination, and arrangement of such networks to satisfy the needs of the developing applications due to extensive demands, high speed, and a great deal of information produced by devices that are connected. Recently, artificial intelligence (AI) has become expected to be implemented as an innovative approach for the development, operational supervision, and automated operation of subsequent generations mobile communications systems. This paper proposes a transmitter-centric semantic communication framework for 6G networks that integrates large language models with reinforcement learning to enable adaptive, context-aware semantic encoding. By jointly optimizing semantic quality, latency, energy consumption, and transmission overhead, the proposed approach significantly outperforms conventional bit-level and learning-based communication schemes under dynamic network conditions.**

***Index Terms*— 5G, 6G, artificial intelligence, autonomous networks, intelligent networks, machine learning, resource allocation.**

I. INTRODUCTION

Sixth generation (6G) wireless connectivity is presently being examined and grown along with 5G cellular networks to exceed the performance of 5G technology. It promises to redefine the way in which communicate and engage with technology by offering groundbreaking levels of connection and speed [1]. Faster transmission speeds, minimal latency, huge device connection, improved energy consumption, and cognitive network administration are the main areas of focus for 6G cellular networks [2]. Multimodal transmission enhanced augmented reality (AR), virtual reality (VR), and fully integrated gaming are several of the groundbreaking revolution that 6G ensure to make possible with transfer rate likely to exceed terabits per second. To satisfy the growing demands for bandwidth and facilitate creative tasks, 6G also is looking at using additional frequency categories, such as terahertz (THz) frequencies [3].

Grenze ID: 01.GIJET.12.2.80

6G, the next generation of wireless connectivity, can transform several sectors, including medical care, education, transportation, and social media, unlocking the door to a more intelligent and highly interconnected world [4, 5].

Artificial intelligence (AI) presents wireless service providers with the possibility to run their internet connections more naturally and economically. By using AI, next-generation systems are expected to grow faster, more reliable, and perform better. Additionally, by the end of 2020, it is anticipated that 53% of service providers will have fully integrated AI into their infrastructure, which is one strategy to solve complexities in networks [6]. Sixth-generation (6G) networks aim to move beyond bit-level transmission toward intelligent, meaning-aware communication. Semantic communication, empowered by large language models (LLMs), enables efficient representation of information but existing methods lack adaptability to dynamic wireless conditions. This paper proposes a transmitter-centric framework that integrates reinforcement learning with LLM-based semantic encoding to enable adaptive and efficient communication for AI-native 6G networks.

Furthermore, two modern AI technologies, machine learning (ML) and deep learning (DL), have represented great attention due to learning proficiency to handle the challenges involved in managing 5G wireless network traffic [7, 8]. In this regard, certain of the most reliable solutions with respect to of confidentiality, safety, and performance improvements for wireless communications are current developments in ML and AI [9, 10]. Additionally, wireless systems should become more resistant to new, complex threats and attacks with dynamic features thanks to deep artificial intelligence and machine learning as shown in fig. 1 [11].

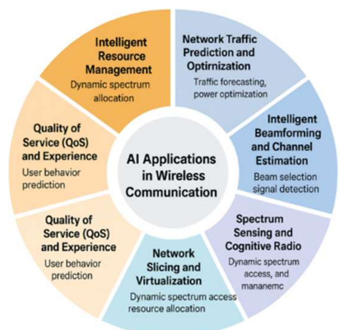

Fig. 1: AI applications in Wireless Networks [11]

II. Related Review

Many significant investigations have examined the link between AI techniques and future connectivity, providing useful data about its functioning and outcomes. Many works discuss wireless communications and other different kinds of artificial intelligence. AI-based optimization techniques in wireless connections involving machine learning (ML) methods such supervised, unsupervised, reinforcement, and transfer learning (TL) constituted the focus of Sheraz et al. [12]. It outlined existing problems that need to be resolved for future generations. An investigation on the significance of AI-based resource allocation was given by Lin and Zhao [13], who also discussed the difficulties and unresolved problems of using AI in forthcoming wireless connectivity. A review of AI-powered decision-making that uses ant colony optimization for both portable and stationary wireless sensor systems inside Internet of Things networks employing a whale optimization gate was provided by Chen et al. [14]. Ramana et al. [15] created a wireless sensor recurrence unit that effectively detects malicious activity. The architecture achieves minimal cost of computation and reliable efficiency by optimizing deep long-short-term-memory (LSTM) parameter values using the whale method. Deep learning applications for wireless systems derived from several layers such as user and application layers, were presented by Mao et al. [16] and have communicated about DL-implementation techniques used in wireless systems.

Sun et al. [17] examined ML and data confidentiality regarding of privacy and security, concentrating on issues like breaching privacy and protecting confidentiality in forthcoming 6G networks. Additionally, it mentioned several ML applications that can both attack and protect privacy. A comprehensive evaluation of IoT security measures based on artificial intelligence algorithms that can offer creative, advanced features to satisfy IoT security needs was described by Wu et al. [18]. Siriwardhana et al. [19] concentrated on investigating how AI may improve security architecture for 6G networks and discussed about the many advantages and difficulties of incorporating cognitive confidentiality and security features into AI's function in 6G systems.

TABLE I. COMPARATIVE STUDY OF VARIOUS AI TECHNIQUES IN 6G NETWORKS [31]

Study	AI Techniques	Focus	Key Contributions	Challenges
Sheraz et al. [12]	Supervised, Unsupervised, Reinforcement ML, Transfer Learning	AI-based caching in wireless networks	Focused on AI techniques in wireless network caching, emphasizing ML algorithms.	Challenges in scaling AI approaches in future generations of wireless networks.
Lin and Zhao [13]	General AI Resource Management Techniques	AI in resource allocation for wireless networks	Provided a consideration on AI-based resource allocation and issues in wireless networks.	Open issues around deployment and scalability in real-world networks.
Chen et al. [14]	Ant Colony Optimization, Whale-Optimized Gate	AI-enabled path selection in IoT networks	Surveyed AI-driven path selection for mobile and static IoT networks using optimization algorithms.	Challenges in optimizing path selection for dynamic IoT networks.
Ramana et al. [15]	Whale Algorithm, LSTM	Attack monitoring in wireless sensor networks	Focused on using whale algorithm for optimizing LSTM hyperparameters for attack detection in sensor networks.	Low computational overhead and real-time performance in attack detection.
Mao et al. [16]	Deep Learning (DL)	DL applications across wireless network layers	Described various DL techniques applied across different layers of wireless networks.	Implementation complexity and computational overhead.
Sun et al. [17]	Machine Learning (ML)	ML and Privacy in 6G networks	Surveyed ML approaches for privacy protection and violation in future 6G networks.	Balancing privacy concerns with AI functionalities.
Wu et al. [18]	ML, DL	AI for IoT security	Discussed IoT security protection using AI algorithms, focusing on meeting IoT security requirements.	Security challenges in highly distributed IoT networks.
Siriwardhana et al. [19]	AI-based Security Framework	AI in 6G security and privacy	Explored the purpose of AI in advanced security configuration in 6G networks, including intelligent security integration.	Integration of AI in security without compromising system integrity.
Bandi and Yalamarthi [20]	ML, AI	Security & Privacy in 6G networks	Introduced a taxonomy of privacy and security analysis related to AI/ML-permitted programs in 6G.	Lack of a unified security model across AI-enabled 6G systems.
Li et al. [21]	AI, Blockchain	AI and Blockchain in 6G	Focused on AI applications within the 6G network architecture, particularly in indoor positioning and AVs.	Data security challenges in AI-powered 6G systems.
Letaief et al. [22]	AI/ML Techniques	Key challenges in 6G	Categorized nine major challenges facing AI/ML integration in 6G wireless networks, such as computation and learning.	Need for interdisciplinary collaboration to address challenges in AI/ML.
Li et al. [23]	AI Techniques	AI in 5G cellular networks	Discussed AI in mobility, resource management, and provisioning for 5G networks.	Open issues in scaling AI techniques for intelligent 5G networks.
Kamble and Shaikh [24]	CNN, DNN, Q-learning, RL, Actor-Critic	Resource allocation in wireless networks	Focused on AI techniques (CNN, DNN, RL, etc.) for dynamic resource allocation in wireless systems.	Real-time resource optimization for varying network conditions.
Pathak et al. [25]	Machine Learning	ML and Blockchain in 6G/IoT	Explores decentralized model sharing, privacy	Does not dissect ML techniques

Additionally, in the framework of 6G systems, Bandi and Yalamarthi [20] provided an organization of several privacy and security problems related to applications provided by AI and ML. Blockchain-based technology as well as artificial intelligence applications in 6G mobile communications were studied by Li et al. [21]. First, a four-phase network including space, air, ground, and underwater sections has been established as part of the 6G design. Two AI applications like AVs and internal positioning, have since been thoroughly investigated. Furthermore, an extensive evaluation has been carried out to demonstrate the increasing importance of confidential information in applications involving AI, backed by an in-depth study that examines into the major factors supporting the development of 6G. Letaief et al. [22] identified and classified nine issues that need to be addressed by the multidisciplinary fields of artificial intelligence, machine learning and wireless networking, particularly regarding wireless networks using 6G. The difficulties include developing remote neural systems, AI computing, and semantics connectivity. In the areas of mobility administration, radio resource management, and allocation management, Li et al. [23] outlined the most basic characteristics of intelligence approaches in 5G mobile networks. Additionally, it highlighted about certain unresolved problems and difficulties with using AI to transform traditional 5G wireless networks into cognitive systems. A variety of allocating resources approaches and strategies that make use of DL techniques, including reinforcement learning, deep neural networks (DNN), convolutional neural networks (CNN), Q learning, and actor-critic, were highlighted by Kamble and Shaikh [24]. The objective is to improve overall system performance by constantly optimizing resource utilization in continuous time. The intersection of machine learning and blockchain was studied in Pathak et al. [25] to increase the 6G IOT network decentralization and security. Noman et al. [26] facilitated collaborative model training without the need to share the data. Thus, although Federated Learning is promising, it is still relatively new to most of the research presented in this survey and considered the challenges to implementing that approach in systems, such as communication overhead and model convergence, was scarce. Sanchez et al. [27] provided a brief overview of RL/DRL for 6G network slicing and described how the techniques can be used for resource scheduling in the context of various constraints. Similarly, Jiang et al. [28] also incorporated mobility and secure connectivity in 6G IoT networks through DRL and Q-learning. Shi et al. [29] presented the RL model by integrating DRL with graph neural networks and algorithm unrolling to achieve distributed optimization in large-scale networks. Puspitasari et al. [30] also highlighted the potential of DL to overcome challenges of massive computation, support reliable communication, and minimize latency.

The reviewed literature shows that a huge demand exists, and still growing, to apply various AI/ML that can address the challenges of 5G and beyond 6G networks in the aspects of adaptability, efficiency, and intelligence. Although the prevailing methods in current research are DL and RL due to their powerful modelling and decision-making ability, FL is also attractive options for communication in a privacy-preserving and optimization-driven manner. Nevertheless, most of the existing studies do not have unified taxonomies or do not discuss on how certain AI techniques (e.g., DL, LSTM, GAN, or DRL) can be mapped to address specific problems in radio resource allocation, such as power control, user association, or latency control. This methodical perspective is essential for the direction of both the research and practical applications of AI based 6G communication systems. The comparative study of several resource management scheduling techniques is described in table I.

III. AI-ENABLED WIRELESS COMMUNICATION

To improve the optimization of 5G and 6G networks, AI-enabled wireless transmission combines machine learning, reinforcement learning, neural networks, and federated learning techniques. Minimal latency, scheduling, dynamic effectiveness along network levels, and cognitive resource management are all made possible by it. AI transforms wireless networks into self-learning, reliable, and creative transmission networks for next-generation applications by utilizing data-driven cognition to increase accuracy, performance, and speed. Resource management enabled by AI in 6G networks is riddled with a series of open issues. With the analysis and decision-making, AI maximizes network efficiency, whereas LLMs improve cognitive ability, semantic awareness, and integrity.

TABLE II. AI-ENABLED 6G WIRELESS TECHNOLOGY

Technology	Description	Key Features	Applications
Terahertz (THz) Communication	Utilizes frequency bands between 0.1–10 THz for ultra-high data rates.	Ultra-fast transmission, high bandwidth, low latency.	Holographic communication, XR, ultra-HD video, tactile internet.
Reconfigurable Intelligent Surfaces (RIS)	Employs programmable meta-surfaces to control electromagnetic wave propagation.	Improved coverage, energy efficiency, adaptive beamforming.	Smart environment, wireless power transfer, indoor/outdoor coverage enhancement.
Blockchain and Distributed Ledger Technologies (DLT)	Provides decentralized, transparent, and secure data management	Data integrity, privacy, trust, and traceability.	Secure data sharing, authentication, network management.
Visible Light Communication (VLC)	Transmits data through LED-based optical signals.	Spectrum efficiency, high speed, interference-free links.	Indoor networks, vehicular communication, smart lighting systems.
Satellite–Terrestrial Integration	Integrates terrestrial and non-terrestrial networks.	Seamless global coverage, reliability, mobility support.	Remote connectivity, disaster recovery, global IoT.
Artificial Intelligence and Machine Learning	Provide cognitive and adaptive control for network functions.	Intelligent automation, predictive analytics, self-optimization.	Resource allocation, network management, anomaly detection, autonomous control.

With previous studies that used deep neural network encoding techniques and more current research using transformers and large language models (LLMs) to represent semantic implications, a semantic communication is now recognized as a possible approach for next-generation wireless technology. Although most current methods lack dynamic adaptability and depend on predefined parameters. Whereas reinforcement learning has already been frequently used in radio resource allocation and management, there is still little integration of it using LLM-based approaches and semantic connectivity. By including reinforcement learning into the semantic encoding process, the present research overcomes this gap and allows for a simultaneous optimization of communication and semantic success. AI-enabled various 6G wireless technology is described in table II.

IV. Proposed Model

For a 6G wireless communications, there is a transmitter-driven semantic communication approach in which cognitive ability and mobility are achieved completely at the wireless transmission node. A transmitter is provided with a reinforcement learning (RL) agent, and a large language model (LLM)-driven semantic encoder which operate closely to oversee both transmission performance and semantic analysis under uncertain network parameters.

At time slot t, the source data $\mathrm{x}_t \in \mathcal{X}$ is mapped to a semantic embedding by the LLM as in (1)

$$\mathrm{s}_t = f_\theta(\mathrm{x}_t), \qquad (1)$$

where $f_\theta(\cdot)$ denotes the LLM with parameters θ. To reduce communication overhead, the semantic embedding is compressed as in (2)

$$\mathrm{z}_t = g_{\rho_t}(\mathrm{s}_t), \qquad (2)$$

where $\rho_t \in (0,1]$ is the semantic compression ratio selected dynamically by the RL agent.

The adaptive semantic communication process is modeled as a Semantic Markov Decision Process (S-MDP) defined by (3)

$$\mathcal{M}_s = \langle \mathcal{S}_s, \mathcal{A}_s, \mathcal{P}_s, \mathcal{R}_s \rangle. \qquad (3)$$

The state space at time t is in (4)

$$\mathcal{S}_s(t) = \{\gamma_t, q_t, \xi_t, e_t\}, \qquad (4)$$

where γ_t is the channel quality indicator (e.g., SNR), q_t is the queue length, ξ_t denotes semantic importance, and e_t represents available transmission energy.

The action space is defined as in (5)

$$\mathcal{A}_s(t) = \{\rho_t, \alpha_t\}, \qquad (5)$$

where ρ_t controls semantic compression and α_t adjusts the LLM attention scaling.

The RL agent aims to learn an optimal policy π^* that maximizes the expected discounted reward as shown in (6)

$$\max_\pi \ \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t R_s(t)\right], \qquad (6)$$

where $\beta \in (0,1)$ is the discount factor and the reward function is defined as in (7)

$$R_s(t) = \lambda_1 Q_{\text{sem}}(t) - \lambda_2 L(t) - \lambda_3 E(t) - \lambda_4 O(t), \qquad (7)$$

with $Q_{\text{sem}}(t)$ denoting semantic quality, $L(t)$ latency, $E(t)$ energy consumption, and $O(t)$ transmission overhead.

An actor–critic architecture:

- Actor: Selects actions (ρ_t, α_t)based on the current state $\mathcal{S}_s(t)$
- Critic: Evaluates long-term expected reward to update the actor

The policy $\pi_\theta$is updated using policy gradient methods as in (8)

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}[\nabla_\theta \log \pi_\theta(\mathcal{A}_s \mid \mathcal{S}_s)(R_s - V_\phi(\mathcal{S}_s))], \qquad (8)$$

where $V_\phi(\mathcal{S}_s)$is the critic's value function.

Algorithm: RL-Assisted Semantic Encoding

- Initialize LLM parameters $\theta$and RL agent
- Observe state $\mathcal{S}_s(t)$
- Select action $\mathcal{A}_s(t) = \{\rho_t, \alpha_t\}$via actor
- Generate semantic embedding $\mathrm{z}_t$using LLM
- Transmit $\mathrm{z}_t$over channel

- ➢ Receive reward $R_s(t)$
- ➢ Update actor–critic parameters using $R_s(t)$
- ➢ Repeat for next time slot

Simulations are conducted in a dynamic 6G wireless environment with time-varying SNR conditions to evaluate the proposed framework. A transformer-based large language model performs semantic encoding, while a reinforcement learning agent adaptively controls semantic compression and attention parameters. The proposed method is compared with bit-level communication, static semantic LLM, and deep learning–based schemes using semantic accuracy, latency, energy consumption, and transmission overhead as performance metrics as described in table III.

TABLE III. SIMULATION PARAMETERS

Parameter	Value
Channel Model	AWGN + Rayleigh fading
Bandwidth	20 MHz
Transmit Power	0–30 dBm
Noise Power	-174 dBm/Hz
Semantic Encoder	LLM, 6 layers, hidden size 512
RL Agent	Actor–Critic, learning rate 0.001, discount factor 0.99
Compression Ratio (ρ_t)	0.1–1.0 (dynamic)
Attention Scaling (α_t)	0.5–1.0 (dynamic)
Simulation Time	10,000 time slots
Metrics / KPIs	Semantic Accuracy, Latency, Energy Efficiency, Spectral Efficiency

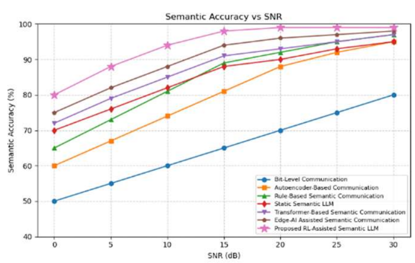

Fig. 2 Semantic Accuracy vs SNR

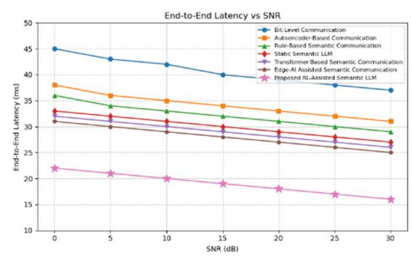

Fig. 3 End-to-End Latency vs SNR

The semantic accuracy outcome over various SNR configurations is shown in Fig. 2. Because of representational fault transmission, bit-level connectivity has limited durability at low SNR, but the use of deep learning algorithms provides little enhancement through developed models. Even though they are less adaptive, transformer-dependent and rigid semantic techniques improve accuracy even more. With an improvement of between 20–25% at low SNR, the proposed RL-powered semantic LLM constantly obtains the maximum semantic accuracy for all SNR ranges. Reinforcement based on modified semantic compression is responsible for this advancement.

Fig. 3 shows a comparison of end-to-end latency. Due to repeated transmissions and fixed encoding patterns, standard bit-level and autoencoder-driven protocols result in more delay. By delivering short, task- specific content, semantic communication greatly reduces latency. In comparison to traditional semantic and deep learning-based precedents, the proposed algorithm reduces latency by up to 30% by constantly modifying semantic noise levels using channel conditions. This shows the potential to be for 6G systems with incredibly low latency.

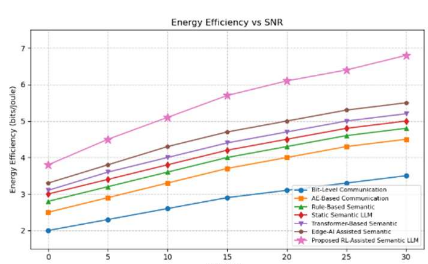

Fig. 4 Energy Efficiency vs SNR

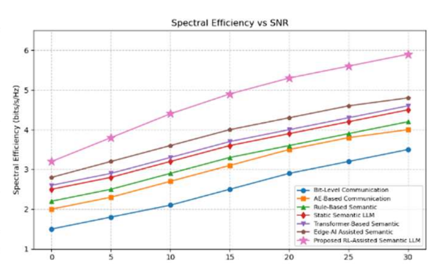

Fig. 5 Spectral Efficiency vs SNR

Fig. 4 shows the energy efficiency results. Through multiple transmissions and processing cost, bit-level and deep learning-driven techniques use more energy. By limiting the volume of statistical information that is transferred, semantic communication enhances energy efficiency. By introducing energy-efficient tasks into the reinforcement learning system, the proposed RL-based strategy significantly improves energy efficiency.
The spectral efficiency gained by different techniques as a ratio of SNR is shown in Fig. 5. Since bit-level communication uses bandwidth excessively, its spectral efficiency is limited. By minimizing irrelevant data while promoting meaning preservation semantic-aware devices enhance performances. The proposed RL-based semantic LLM outperforms all of them in terms of spectrum efficiency, particularly for intermediate to high SNR values. This shows how adaptable semantic encoding improves bandwidth consumption.

V. Future Trends

Integration of AI enables wireless networks with 6G to become cognitive, self-managing, and adaptable. These systems can achieve better user experience, increase energy consumption, and maximize energy consumption on an individual basis. Additionally, AI can help future wireless networks to promote preservation, enhanced safety, and ongoing maintenance.
The six-generation use of AI and LLM makes innovative, flexible resource management conceivable. With the analysis and decision-making, AI maximizes network efficiency, whereas LLMs improve cognitive ability, semantic awareness, and integrity.
Through increasing speed, reducing network congestion, and allowing context-sensitive conversation, they have cooperated to develop wireless networks using 6G that are reliable, effective, and self-organizing to support future cognitive connections. Future trends and research directions for AI in 6G wireless networks is described in table IV.

TABLE IV. FUTURE TRENDS AND RESEARCH DIRECTIONS FOR AI IN 6G WIRELESS NETWORKS.

Trend/Direction	Description
Intelligent Spectrum Management	AI optimizes dynamic spectrum use for efficiency.
AI-Driven Beamforming	Enhances coverage and performance in mm-Wave bands.
Autonomous Networks	Enables self-healing and self-optimizing 6G systems.
Quantum-Assisted AI	Combines AI with quantum computing for faster optimization.
AI-Enabled Satellite Networks	Extends connectivity for remote areas and disaster recovery.
AI-Enhanced Network Slicing	Provides adaptive slices for different industrial applications.
Distributed ML	Improves scalability and real-time learning across edge devices.

V. Conclusion

Next-generation wireless transmission is increasingly powered by artificial intelligence, particularly as 6G connections are becoming more common. Large language models for dynamic semantic representation were used in this work to offer a RL-based semantic communication system for 6G wireless networks. The proposed approach evolves with semantic compression along with channel environment and function needs, in opposed to bit-specific and conventional semantic methods.
Semantic accuracy, latency, spectrum efficiency, and energy efficiency all significantly improve over a range of SNR rates, according to simulation results. Specifically, the proposed method reduces latency by about 30% and improves semantic accuracy by up to 25% when compared with baseline techniques. Efficient technology evolution is proven by outstanding achievement under evolving platforms and more rapid learning convergence. These results indicate the great potential of semantic LLMs reinforced by reinforcement learning for cognitive 6G communications. The subsequent studies will concentrate on simplified model implementation, cross-layer optimization, and multi-user circumstances.

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