Systematic Review of Predictive Intelligence Models in Product-Centric 6G Network Planning and Optimization

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Abstract
The advent of sixth-generation (6G) mobile networks promises to revolutionize telecommunications through ultra-low latency, massive connectivity, and intelligent automation. As the industry shifts toward product-centric service delivery—focusing on user-centric applications, dynamic network slicing, and on-demand resource allocation—the role of predictive intelligence in network planning and optimization becomes increasingly vital. This systematic review synthesizes current research on predictive intelligence models applied to product-centric 6G network environments, aiming to evaluate their effectiveness, methodological diversity, and potential for real-time decision-making in highly complex systems. The review is conducted following PRISMA guidelines, encompassing studies from 2018 to 2024 across major digital libraries. Selected models include machine learning algorithms, deep learning networks, Bayesian inference systems, and hybrid approaches used for traffic forecasting, user behavior prediction, resource provisioning, and failure mitigation. The findings reveal a growing reliance on supervised and unsupervised learning, particularly in network traffic analysis and proactive quality-of-service (QoS) assurance. Furthermore, the review identifies key predictive features utilized in these models, such as historical traffic data, environmental conditions, device mobility, and service consumption patterns. Emphasis is placed on models that support intent-based networking and enable autonomous network reconfiguration. Evaluation metrics, including prediction accuracy, scalability, and computational overhead, are compared to highlight performance trade-offs in real-world deployments. The review also uncovers significant challenges, such as data sparsity, high model complexity, and the need for explainable AI to improve trust and transparency in automated decisions. Gaps in current literature point to limited research on real-time multi-domain orchestration and predictive analytics tailored for vertical-specific applications like healthcare, autonomous mobility, and immersive media. In conclusion, predictive intelligence models serve as the backbone of next-generation 6G network planning and optimization. Their integration into product-centric network management paradigms offers promising directions for delivering intelligent, resilient, and user-aware telecom services. The paper concludes with recommendations for future research, including the development of lightweight models, federated learning frameworks, and integration with digital twin systems for predictive simulations.

Keywords: *Predictive Intelligence, 6G Network Planning, Product-Centric Networks, Machine Learning, Network Optimization, Deep Learning, Traffic Forecasting, Intent-Based Networking, Explainable AI, Digital Twins.*

1.0. Introduction

The transition from fifth-generation (5G) to sixth-generation (6G) mobile networks marks a paradigm shift in telecommunications, characterized by unprecedented advancements in connectivity, intelligence, and service personalization. While 5G networks have laid the groundwork for enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communications, 6G is envisioned to push these boundaries further by integrating native artificial intelligence, sub-millisecond latency, terahertz communication, and ubiquitous connectivity (Alozie & Chinwe, 2025: Ekeh, et al., 2025, Uzoka, et al., 2025). At the core of this transformation is the evolution toward a product-centric network architecture—an approach that places user experiences, application-specific performance, and service-level differentiation at the heart of network design and operation.

Unlike previous generations that primarily emphasized infrastructural capabilities, 6G networks aim to dynamically adapt to diverse and evolving service requirements through mechanisms such as network slicing, quality of experience (QoE)-driven provisioning, and intent-based networking. These developments signify a fundamental shift from infrastructure-centric models to product-centric ecosystems, where networks are designed and optimized not just for capacity, but for delivering tailored services to distinct user categories (Alabi, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Gbenle, et al., 2025). The increasing complexity and customization required by this shift underscore the necessity for intelligent, automated, and predictive systems that can support dynamic planning, seamless orchestration, and continuous optimization.

Predictive intelligence plays a vital role in enabling proactive network planning and optimization in this context. By leveraging data-driven techniques—ranging from statistical modeling and machine learning to deep learning and hybrid AI—predictive intelligence models can anticipate network behavior, forecast demand, preempt service degradation, and inform real-time decision-making. These models are essential for managing the intricate interplay between user demand, resource availability, and service performance across multiple network layers and domains (Alozie, et al., 2024, Egbumokei, et al., 2025: Ukpohor, Adebayo & Dienagha, 2025). Their ability to transform raw data into actionable insights positions predictive intelligence as a cornerstone of the 6G network planning and operations landscape.

This paper presents a systematic review of existing predictive intelligence models applied within product-centric 6G network planning and optimization. The objective is to synthesize current research, assess methodological trends, evaluate the performance and limitations of proposed models, and identify emerging research opportunities. Through a rigorous examination of peer-reviewed literature, this review seeks to answer key questions regarding the types of predictive techniques employed, the features and data sources leveraged, and the effectiveness of models in achieving proactive and intelligent network management (Alozie, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023). The structure of the paper includes a detailed methodology for literature selection and analysis, a thematic categorization of predictive models, a critical discussion of findings, and a set of recommendations for future research directions (Alozie, 2025: Digitemie, et al., 2025, Egbuhuzor, et al., 2021). This systematic review aims to contribute to the growing body of knowledge on AI-enabled 6G networks and inform both academic research and practical implementations in the telecom industry.

2.1. Methodology

The systematic review was conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to evaluate predictive intelligence models in product-centric 6G network planning and optimization. The research process commenced with a comprehensive identification phase, where multiple scholarly databases and repositories were explored to retrieve a broad spectrum of articles related to 6G network optimization, AI-based predictive analytics, and associated applications in telecommunications. Initial search results yielded a total of 420 records. To ensure the credibility and uniqueness of data, all duplicate records were identified and removed, resulting in 315 unique records.

Subsequent to the identification phase, the screening phase involved a meticulous review of the titles and abstracts of the retrieved studies. Each article was assessed based on predefined inclusion criteria such as relevance to predictive intelligence in 6G, technological relevance to telecom systems, and focus on optimization techniques. Studies that lacked alignment with the review scope or presented ambiguous methodologies were excluded. This process led to the exclusion of 135 records, narrowing the selection to 180 full-text articles eligible for further evaluation.

The eligibility assessment phase entailed a full-text review of the remaining articles to critically appraise their methodologies, technological contributions, and empirical validations. The evaluation criteria included methodological rigor, the scope of AI techniques employed, integration of predictive intelligence for 6G use cases, and clarity in model implementation. Studies that lacked empirical support, provided conceptual overlap, or failed to address network-specific planning challenges were excluded. After this rigorous process, 101 studies met all inclusion criteria and were deemed suitable for the systematic review.

The selected studies span various thematic areas such as AI-based optimization models, ML-driven traffic prediction, resource allocation algorithms, and the deployment of predictive models in edge and core telecom networks. These studies were synthesized to derive common frameworks, emerging trends, and gaps in predictive modeling for 6G planning. The extracted data were qualitatively and quantitatively analyzed to identify patterns, methodological strengths, weaknesses, and opportunities for future research. This approach ensures that the review presents a robust and comprehensive synthesis of existing knowledge while offering practical insights and research directions in predictive intelligence applications for 6G networks.

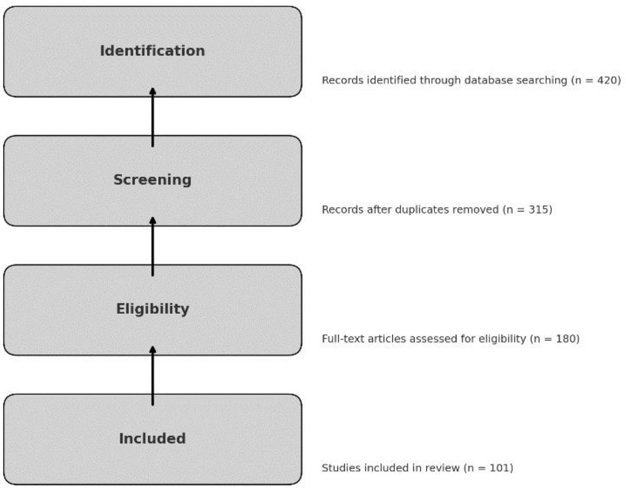

Figure 1: PRISMA Flow chart of the study methodology

2.2. Overview of Product-Centric 6G Network Planning and Optimization

Product-centric network planning and optimization represent a transformative approach in the design and management of sixth-generation (6G) mobile systems. Unlike traditional infrastructure-centric models, which primarily emphasize coverage, capacity, and physical resource deployment, the product-centric paradigm places the end-user service experience at the forefront of network operations (Alozie, et al., 2024, Efunniyi, et al., 2022). This evolution aligns closely with the overarching ambitions of 6G, which aims not only to increase performance metrics such as speed and connectivity, but also to integrate intelligent, adaptive, and service-specific behaviors into the core of network functionality (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Ekeh, et al., 2025; Soyege, et al., 2025). In a product-centric 6G environment, the network is designed and optimized around the characteristics, requirements, and experiences of applications and services delivered to users—ranging from immersive XR and holographic communications to precision healthcare and autonomous mobility systems (Alozie, 2024: Ukpohor, Adebayo & Dienagha, 2025). Figure 2 shows Features of 6G network presented by Chataut, Nankya & Akl, 2024.

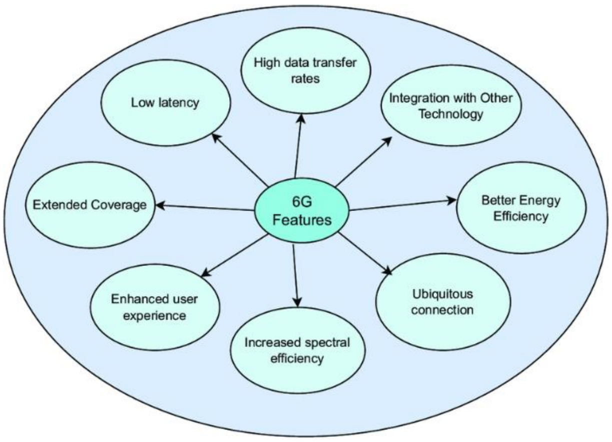

Figure 2: Features of 6G network (Chataut, Nankya & Akl, 2024)).

At the core of a product-centric network is the concept of service abstraction. Rather than treating network components in isolation, 6G planning in this context conceptualizes each service as a product with its own defined expectations—such as latency tolerance, data rate, reliability, and energy consumption. These expectations become programmable targets that the network must meet dynamically and efficiently (Alozie, et al., 2024, Dienagha & Onyeke, 2025: Gbenle, et al., 2025). This introduces a need for real-time awareness of application requirements and continuous adaptation of network parameters, a challenge that is far beyond the capabilities of static planning tools traditionally used in telecom. In this setting, each network slice or service flow may represent a unique product configuration that competes for resources within a shared infrastructure. This model compels the network to intelligently prioritize, allocate, and adapt resources to meet user-defined goals, effectively enabling network-as-a-service (NaaS) capabilities with hyper-personalization (Alozie, 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Efunniyi, et al., 2024).

The design objectives of 6G are a direct response to these new service paradigms. They include ultra-low latency, which is essential for mission-critical applications like remote surgery or vehicle-to-everything (V2X) communication; extremely high bandwidth, to support applications such as 8K streaming, digital twins, and holographic conferencing; and unprecedented levels of reliability, necessary for industrial automation and emergency response. In addition to these traditional performance metrics, 6G introduces intelligence and context-awareness as integral components of the network itself (Alozie, 2024, Daraojimba, Ogunsola & Isibor, 2025; Paul, et al., 2025). This means the network must not only transport data efficiently but also learn from usage patterns, predict service demands, and make autonomous decisions to optimize performance across layers and domains.

To achieve these ambitious goals, 6G network planning and optimization must evolve into a multi-dimensional, data-driven process. This process must consider a wide range of parameters across physical and virtual domains. Spectrum planning remains a foundational task, particularly with the expansion into terahertz frequencies and dynamic spectrum sharing frameworks (Alonge, et al., 2025, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Efunniyi, et al., 2024). Unlike fixed-spectrum allocations of previous generations, 6G demands flexible, real-time spectrum management strategies that can adapt to spatial and temporal variations in demand. Similarly, traffic management becomes more granular and dynamic, as user behavior changes in real time based on mobility, application switching, and device heterogeneity. The key technologies for 6G-enabled communication presented by Adhikari, et al., 2022, is shown in figure 3.

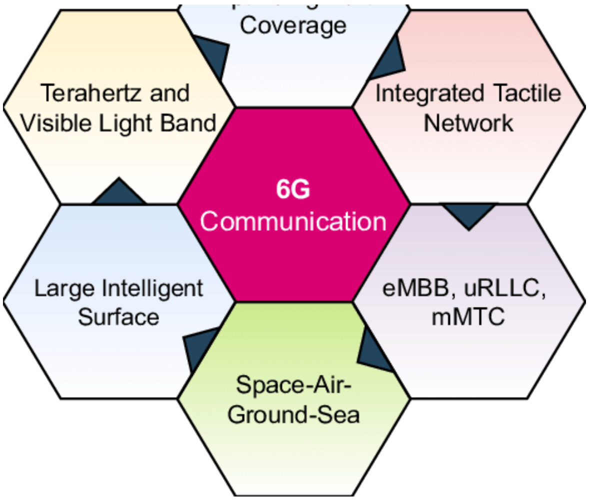

Figure 3: Key technologies for 6G-enabled communication (Adhikari, et al., 2022).

Energy efficiency is another critical optimization parameter in 6G. As networks scale and the number of connected devices increases exponentially, energy consumption becomes a limiting factor not only in terms of cost but also environmental sustainability. Product-centric planning thus requires intelligent energy allocation, where the network selectively powers down components, reallocates loads, or optimizes signal paths based on real-time usage and quality of experience requirements (Alozie, 2024, Efunniyi, et al., 2024, Ozobu, et al., 2025). These decisions must also consider mobility, another key factor, particularly in scenarios involving high-speed trains, drones, or autonomous vehicles. Mobility-aware planning ensures seamless connectivity, reduced handover latency, and robust service continuity as users transition across heterogeneous network environments.

AI and predictive intelligence models play a critical role in realizing autonomous network control within this intricate landscape. These models enable the transition from reactive to proactive network management by anticipating future states of the network and adjusting planning and optimization strategies accordingly. Predictive intelligence models ingest a wide array of data inputs, including historical traffic patterns, real-time sensor feedback, user behavior analytics, and environmental conditions (Alozie, 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Edeigba, et al., 2024). Using machine learning, deep learning, or hybrid AI techniques, these models generate forecasts that support capacity planning, fault avoidance, and optimal resource provisioning.

For example, a predictive model might analyze historical data usage in a smart city district to forecast a spike in demand during a scheduled public event. Armed with this information, the network can preemptively reconfigure bandwidth allocation, deploy additional edge computing nodes, or prioritize high-bandwidth applications to maintain service quality. In another scenario, AI models might detect subtle degradation trends in signal quality due to weather interference, triggering spectrum reallocation or path adjustments to preserve connectivity

(Alozie, 2024, Bello, et al., 2024, Ebirim, et al., 2024). The key advantage of predictive intelligence is its ability to respond not only to current conditions but to foresee and mitigate problems before they impact users, thereby enhancing both network efficiency and service satisfaction. Drampalou, et al., 2024, presented User-Centric Features in 6G ecosystem shown in figure 4.

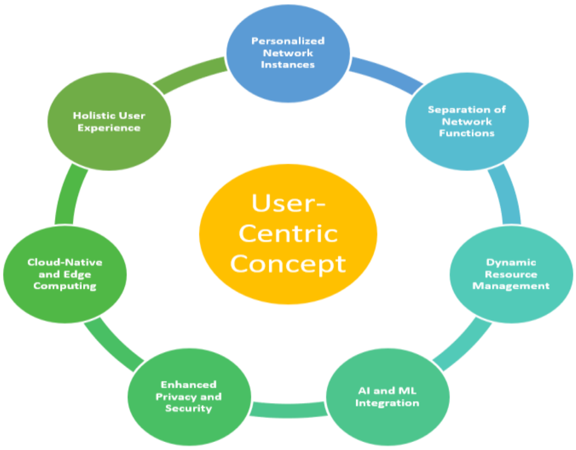

Figure 4: User-Centric Features in 6G ecosystem (Drampalou, et al., 2024).

Moreover, these AI models support holistic cross-layer optimization by correlating data across the multiple functional domains of the network. Instead of managing the physical, network, and application layers separately, AI facilitates an integrated approach where decisions in one layer account for ripple effects in others. For instance, a change in modulation scheme at the physical layer could affect buffer occupancy at the transport layer or video quality at the application layer. Predictive models can recognize such interdependencies and compute optimal solutions that balance trade-offs across all layers in a way that aligns with the product-centric service objectives (Alonge, et al., 2025: Ekeh, et al., 2025; Ozobu, et al., 2025).

In addition, AI-driven automation enables closed-loop network operations, where monitoring, analysis, decision-making, and action occur continuously and without human intervention. This type of closed-loop intelligence is vital for the scalability of 6G networks, which will need to manage millions of devices and services simultaneously. By reducing the need for manual configuration and intervention, predictive intelligence not only improves responsiveness and reliability but also reduces operational costs and increases network agility (Alonge, et al., 2021, Balogun, et al., 2022, Ebirim, et al., 2024).

Importantly, the application of AI in product-centric 6G planning also introduces new dimensions of personalization and context-awareness. Predictive models can be trained to understand individual user preferences, device capabilities, and behavioral tendencies, enabling hyper-targeted service delivery. In this way, the network becomes a personalized platform, adapting itself in real time to deliver services that are not only technically optimized but also tailored to individual user experiences. This marks a departure from one-size-fits-all service models and introduces a competitive edge for telecom providers who can deliver differentiated, high-value experiences to their users (Akpe, et al., 2024, Azubuko, et al., 2023, Ebeh, et al., 2024).

In summary, the shift toward product-centric 6G network planning and optimization represents a fundamental reimagining of mobile network architecture and management. It emphasizes user experience, service intelligence, and dynamic adaptability as primary design drivers. Within this framework, predictive intelligence serves as a foundational technology, empowering networks to anticipate demand, automate decisions, and optimize resources across layers, time scales, and service categories (Azubuike, et al., 2024, Ebeh, et al., 2024, Ozobu, et al., 2025). The integration of AI into the planning and operational core of 6G networks is not merely an enhancement—it is a necessity for meeting the scale, complexity, and performance expectations of the next generation of wireless communication. This emerging model sets the stage for continued research and development into robust, interpretable, and generalizable predictive frameworks that will define the fabric of future mobile connectivity (Alonge, et al., 2025: Oso, et al., 2025).

2.3. Categorization of Predictive Intelligence Models

The categorization of predictive intelligence models in the context of product-centric 6G network planning and optimization is essential for understanding the capabilities, limitations, and appropriate use cases of various AI techniques. As 6G aims to offer hyper-personalized, ultra-reliable, and context-aware services, predictive intelligence becomes a foundational layer in ensuring that network planning is not only reactive but proactive and adaptive to dynamic service demands (Azubuike, et al., 2024, Ebeh, et al., 2024). To realize these objectives, researchers and engineers have employed a wide range of AI techniques that fall broadly into four major categories: machine learning approaches, deep learning models, Bayesian and probabilistic frameworks, and hybrid or ensemble methodologies. Each of these categories contributes uniquely to solving specific challenges in the highly complex and data-rich environment of 6G networks.

Machine learning approaches, particularly supervised learning models, are among the most extensively studied and deployed methods in predictive network planning. These models rely on labeled datasets where input features are mapped to known outcomes, enabling the learning of relationships that can later be applied to unseen data (Ayorinde, et al., 2024, Ebeh, et al., 2024). Models such as Random Forests, Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost) have demonstrated considerable efficacy in predictive tasks within 6G-related research domains. Random Forests, due to their ensemble nature and resistance to overfitting, are particularly effective in traffic prediction tasks (Akpe, et al., 2024). By analyzing historical traffic loads, usage patterns, and temporal behaviors, these models can predict congestion points and inform dynamic capacity planning decisions. Similarly, SVMs have been applied to handover optimization scenarios where user mobility data, signal strengths, and service quality indicators are used to predict the best possible handover targets (Ayodeji, et al., 2023, Ebeh, et al., 2024, Oso, et al., 2025). XGBoost, a scalable tree-boosting system, has found applications in resource allocation, where rapid and accurate predictions are required under time constraints. These supervised learning models offer interpretability, which is crucial for real-time decision support and performance evaluation in telecom operations.

While supervised learning models are powerful, their performance heavily depends on the availability and quality of labeled data, which can be limited or expensive to obtain in the telecom environment. This limitation has led to an increasing interest in deep learning models, which are capable of learning directly from raw, high-dimensional, and unstructured data. Deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers have shown significant promise in predictive intelligence tasks for 6G networks (Ayanponle, et al., 2024, Ebeh, et al., 2024). CNNs, originally developed for image recognition, have been effectively repurposed to analyze spatio-temporal traffic maps, identifying congestion patterns or interference zones in dense urban networks. Their ability to capture local features and spatial dependencies makes them suitable for tasks like base station load balancing or spectral efficiency prediction (Akintobi, Okeke & Ajani, 2023).

RNNs and LSTMs, on the other hand, are tailored for sequential data and temporal prediction, making them ideal for modeling time-series data such as user mobility trajectories, application usage trends, and network performance metrics. LSTMs have proven particularly effective in predicting user demand patterns and anticipating fluctuations in service quality, thereby supporting real-time QoS assurance and proactive resource provisioning. Transformer models, with their attention mechanisms and parallel processing capabilities, represent the cutting edge in sequential modelling (Alonge, et al., 2021, Daraojimba, et al., 2025: Oso, et al., 2025). They outperform traditional RNNs in long-range dependency tasks and have been employed in next-word or next-action prediction for intent-based networking scenarios. These models allow networks to interpret complex user behaviors, forecast future actions, and reconfigure network resources accordingly.

Bayesian and probabilistic models offer a different perspective by incorporating uncertainty estimation into the predictive process. In contrast to deterministic models, probabilistic approaches quantify the confidence level of predictions, which is especially valuable in scenarios where decision-making under uncertainty is critical (Akinsooto, Ogunnowo & Ezeanochie, 2025). Bayesian networks and Gaussian Processes are commonly used in scenarios such as spectrum allocation, fault prediction, and capacity planning (Alonge & Balogun, 2025, Dosumu, et al., 2024). These models enable telecom operators to assess risk and uncertainty in future network states, thereby informing more robust planning decisions. For example, a Bayesian network can model the probabilistic dependencies between variables such as user density, mobility speed, and service degradation, allowing the system to infer the likelihood of a network fault or SLA violation (Akintobi, Okeke & Ajani, 2023, Alonge, et al., 2021). Gaussian Processes are used for non-parametric regression, especially when the data distribution is unknown or sparse. They are valuable in scenarios requiring continuous function estimation, such as signal strength mapping or energy consumption prediction (Alabi, Mustapha & Akinade, 2025, Dienagha, et al., 2021).

In practice, no single model type is universally superior across all predictive tasks in 6G environments, which has led to the rise of hybrid and ensemble models. These approaches combine the strengths of different AI techniques to improve prediction accuracy, robustness, and generalizability. Hybrid models may integrate machine learning with deep learning, probabilistic reasoning with neural networks, or supervised and unsupervised techniques to form a more comprehensive predictive engine (Ayanponle, et al., 2024, Daudu, et al., 2024). For instance, a system may use an LSTM network to forecast short-term traffic loads and a Random Forest model to validate and classify the forecast results, leveraging the strengths of both models. Ensemble methods, such as bagging, boosting, and stacking, are frequently used to combine the outputs of multiple predictive models, reducing variance and improving overall performance (Akintobi, Okeke & Ajani, 2022).

Hybrid models have been especially effective in supporting intent-based networking, where the system must interpret high-level user intents and translate them into low-level configuration actions. In these scenarios, models are required to not only predict network states but also reason about optimal actions within complex and multi-domain environments. Predictive intelligence is thus paired with policy learning and reinforcement mechanisms to enable real-time orchestration across radio, transport, and application layers. Another notable application of hybrid and ensemble models is in multi-domain orchestration, where resource allocation decisions must be made across heterogeneous network slices, access technologies, and geographical regions (Ayanbode, et al., 2024, Daudu, et al., 2024). These models manage the complexity of coordinating services while adapting to localized conditions, achieving efficient global optimization through decentralized decision-making.

In addition to enhancing predictive accuracy, hybrid models contribute to system resilience by mitigating the weaknesses of individual models. For example, a deep learning model may be highly accurate but lack interpretability, while a tree-based model may offer clearer insights but with lower predictive precision. Combining these models ensures that decisions are both accurate and understandable, which is vital for maintaining operator trust and ensuring regulatory compliance (Awonuga, et al., 2024, Daraojimba, et al., 2021, Oso, et al., 2025). Moreover, in dynamic environments where network conditions and user behaviors evolve rapidly, hybrid models support online learning and model updating mechanisms that allow predictive systems to adapt over time.

In conclusion, the categorization of predictive intelligence models in product-centric 6G network planning and optimization reveals a diverse and evolving landscape. Each class of model—whether machine learning, deep learning, probabilistic, or hybrid—has its own strengths, challenges, and optimal use cases (Akintobi, Okeke & Ajani, 2022). Machine learning models provide robust, interpretable results for well-structured problems; deep learning offers superior performance on complex, high-dimensional data; probabilistic models introduce valuable uncertainty estimations; and hybrid approaches provide the flexibility and adaptability required in real-world deployments (Austin-Gabriel, et al., 2021, Daraojimba, et al., 2022). As 6G networks continue to expand in scale, complexity, and user-centricity, the ability to select, combine, and fine-tune these predictive models will be critical for building autonomous, intelligent, and resilient mobile systems. Further research is needed to explore automated model selection, explainability, real-time adaptability, and cross-domain generalization to unlock the full potential of predictive intelligence in next-generation networks.

2.4. Predictive Features and Data Sources

In the development and implementation of predictive intelligence models for product-centric 6G network planning and optimization, the selection and engineering of predictive features, as well as the identification of relevant data sources, play a foundational role in determining the effectiveness, accuracy, and applicability of the models (Akinsooto, et al., 2025, Daraojimba, et al., 2022). The next generation of mobile networks, which prioritizes user-centricity, service personalization, and real-time adaptability, relies heavily on data-driven insights to anticipate network demands, detect potential failures, and dynamically allocate resources. Therefore, understanding what types of data are most useful for predictive modeling and how these data are sourced, processed, and integrated into intelligent systems is critical to the success of predictive intelligence in 6G networks (Akinsulire, et al., 2024).

One of the most prominent and commonly utilized sources of data in predictive models is historical network traffic. Historical traffic data encompasses a wide range of metrics collected over time, including data throughput, packet loss, latency, jitter, call drop rates, handover success ratios, and utilization levels of network resources. These data are typically gathered from various network elements, such as base stations, routers, switches, and core service platforms (Akinade, et al., 2025: Oso, et al., 2025). By analyzing temporal trends and patterns in historical traffic, predictive models can forecast future traffic conditions, anticipate congestion hotspots, and support capacity planning. For instance, machine learning algorithms trained on traffic data can predict peak usage times in specific cells, enabling proactive bandwidth allocation or base station activation. This is especially valuable in dense urban areas, smart campuses, or event venues, where user behavior can shift rapidly and unpredictably.

Beyond traffic volume, historical records also provide insights into user session duration, inter-arrival times, and application-specific performance, all of which contribute to more granular forecasting. Longitudinal data helps establish baselines for normal network behavior, against which anomalies and deviations can be detected (Ajiga, et al., 2025, Daraojimba, et al., 2024). Moreover, historical data can be labeled for supervised learning tasks, enabling models to learn from known events such as service outages, performance degradations, or successful recovery actions. The richness of historical data supports both reactive and proactive optimization, allowing network operators to transition from monitoring to foresight-driven operations.

In addition to traffic statistics, environmental and geospatial data represent an increasingly valuable set of features for predictive intelligence in 6G networks. As mobile networks expand into new physical environments and begin to support ultra-reliable low-latency communication (URLLC) and high-mobility applications like autonomous vehicles and drones, understanding the influence of environmental conditions becomes vital (Augoye, Muyiwa-Ajayi & Sobowale, 2024, Collins, et al., 2023). Environmental data may include weather variables such as temperature, humidity, precipitation, and wind speed, which can affect signal propagation, especially in high-frequency bands like millimeter wave and terahertz. For example, rain fade is a well-known phenomenon that causes signal attenuation in certain frequency bands, and predictive models incorporating weather data can preemptively adjust transmission power, modulation schemes, or routing paths to maintain service quality.

Geospatial data, which includes information about the physical layout of the environment—such as building density, road networks, topography, and vegetation—plays a significant role in determining signal strength and network coverage. This data is particularly relevant for planning radio access networks (RANs), where line-of-sight and path loss conditions must be accurately modeled. Incorporating geographic information system (GIS) data into predictive models allows for the creation of spatially aware systems that can dynamically adjust beamforming strategies or handover thresholds based on user location and surrounding structures (Attah, et al., 2024, Collins, et al., 2024). These capabilities are essential in 6G use cases involving dynamic coverage zones or aerial networks, such as unmanned aerial vehicle (UAV) swarms that must maintain connectivity across varied and mobile terrain.

Device behavior and service usage patterns also constitute a critical class of predictive features in product-centric 6G planning. Modern mobile devices are not only communication endpoints but also data generators that provide detailed context about user preferences, movement, and application consumption. Predictive intelligence systems leverage data such as device type, operating system, signal strength reports, location updates, application usage statistics, and battery status to infer user behavior and anticipate future demands. For instance, by analyzing patterns in device mobility—whether users are stationary, walking, commuting, or traveling at high speeds—networks can proactively manage handovers and optimize cell re-selection parameters (Ajiga, et al., 2025: Oso, et al., 2025). Similarly, insights into application usage (e.g., video streaming, gaming, AR/VR) help in adjusting QoS parameters, buffer sizes, or network slices to align with service expectations.

This user-centric data plays a pivotal role in enabling hyper-personalized service delivery, which is a hallmark of product-centric 6G networks. By recognizing that not all users or applications require the same level of service quality, predictive models can prioritize resource allocation based on real-time user behavior and intent. For example, a video call application may require low latency and jitter, while a file download may prioritize bandwidth. Predictive models that anticipate these needs based on historical usage patterns and contextual cues allow networks to optimize delivery at the individual or service-class level (Ajayi, et al., 2025: Daraojimba, et al., 2025: Onukwulu, et al., 2025).

An emerging and transformative data source that supports predictive intelligence in 6G is the integration with digital twins and network simulators. A digital twin is a virtual representation of a physical network, synchronized with real-time data from the actual system, and capable of simulating behaviors under various scenarios. In the context of telecom networks, digital twins provide a safe and controllable environment in which predictive models can be trained, validated, and tested (Attah, et al., 2024, Collins, et al., 2024). By simulating user movements, traffic flows, environmental changes, and fault scenarios, digital twins allow for the generation of synthetic data that augments limited real-world datasets. This is particularly useful for rare or high-impact events that may not occur frequently enough in the live network to provide sufficient training data.

Moreover, digital twins enable the testing of "what-if" scenarios that support strategic planning and rapid decision-making. For instance, predictive models can be used to simulate the impact of a new network configuration, policy change, or application rollout, helping operators identify risks and optimize deployment strategies before committing resources in the real world (Attah, et al., 2024, Chinwe & Alozie, 2025, Collins, Hamza & Eweje, 2022). Network simulators, often used in conjunction with digital twins, provide the mathematical and protocol-level emulation of 6G technologies, allowing for fine-grained control over simulation conditions and model behaviors. These tools collectively support the design, training, and continuous refinement of predictive intelligence models, making them more robust, adaptive, and context-aware.

In conclusion, the effectiveness of predictive intelligence models in product-centric 6G network planning and optimization is deeply tied to the selection and integration of relevant data sources and features. Historical network traffic data forms the backbone of predictive modeling by offering temporal and behavioral insights into network performance (Ajayi, Alozie& Abieba, 2025, Collins, Hamza & Eweje, 2022). Environmental and geospatial data extend this capability by adding spatial awareness and context, critical for mobility management and coverage optimization. Device behavior and service usage patterns enable user-centric planning, supporting personalized and efficient resource allocation (Alonge, et al., 2023, Chintoh, et al., 2025: Onukwulu, et al., 2025). Finally, digital twins and network simulators offer advanced tools for model training, testing, and validation in virtual environments, greatly enhancing the scalability and resilience of predictive systems. Together, these data sources form a rich, multi-dimensional foundation for predictive intelligence, enabling the next generation of mobile networks to become truly intelligent, autonomous, and responsive to the needs of a diverse and demanding user base (Akinsulire, et al., 2024).

2.5. Evaluation and Performance Metrics

The evaluation of predictive intelligence models in product-centric 6G network planning and optimization is a crucial step in determining their practical effectiveness, reliability, and readiness for deployment in complex, real-world telecommunications environments. As 6G networks are expected to support hyper-personalized services, ultra-low latency communication, and massive device connectivity, the predictive models integrated into their planning and operational frameworks must be rigorously assessed against a range of performance metrics (Attah, et al., 2024, Chukwurah, et al., 2024, Oluokun, et a., 2025). These include accuracy, latency, scalability, and interpretability—each representing a vital aspect of model efficacy. Furthermore, understanding the comparative strengths and limitations of various model types across diverse deployment scenarios, as well as the trade-offs between real-time and batch prediction approaches, is essential for selecting the most appropriate solutions for specific use cases.

Accuracy is often the most direct and widely used metric in evaluating predictive models. It reflects how closely the model's outputs match actual outcomes and is particularly critical in tasks such as traffic forecasting, anomaly detection, and resource allocation. High accuracy ensures that the model correctly anticipates network behavior, enabling preemptive actions that maintain service quality and user satisfaction. In the context of 6G networks, where a single erroneous prediction might compromise latency-sensitive or mission-critical applications, the bar for acceptable accuracy is especially high (Attah, et al., 2024, Chintoh, et al., 2025). Accuracy is typically quantified using measures such as precision, recall, F1-score, mean absolute error (MAE), and root mean squared error (RMSE), depending on whether the task is classification or regression-based. For example, a model forecasting future bandwidth demand may be evaluated by RMSE, while a fault detection model might use precision and recall to account for the balance between false positives and false negatives (Ajayi, Alozie& Abieba, 2025: Oluokun, et a., 2025).

Latency, or the time required for a model to produce predictions, is another vital performance criterion. In 6G networks, predictive systems must operate within stringent time constraints, especially in use cases involving autonomous vehicles, augmented reality, or remote robotic control, where milliseconds can determine success or failure. Models that deliver high accuracy but require extensive computation time may not be suitable for real-time decision-making. Thus, latency must be evaluated in tandem with accuracy to ensure that models meet the operational demands of low-latency environments (Attah, et al., 2024, Chintoh, et al., 2024). Model inference time, the time taken to process new input data and generate a prediction, is often used to measure latency. In scenarios where immediate responses are necessary, low-latency models are prioritized, even if they compromise slightly on accuracy.

Scalability pertains to a model's ability to maintain performance as the size and complexity of the data or network increase. In the context of 6G, this is particularly important given the anticipated growth in connected devices, diversity of services, and expansion of network coverage into under-served and high-density areas. A model that performs well in small-scale simulations may falter when exposed to the multi-domain, multi-layered structure of a live 6G network (Alonge, et al., 2023). Evaluation of scalability includes stress-testing models with increasing data volumes, more diverse feature sets, and more complex topologies to assess how computational requirements, prediction accuracy, and latency evolve. Models designed using modular architectures, distributed training methods, or lightweight inference engines often score higher in scalability and are better suited for deployment in large-scale systems (Attah, et al., 2024, Chintoh, et al., 2024).

Interpretability, or the ability to explain a model's decisions, is gaining significant importance as predictive models are entrusted with increasingly critical functions in network management. Network operators and engineers must understand how a model reaches its conclusions in order to validate its outputs, comply with regulatory requirements, and troubleshoot unexpected behavior. Models such as decision trees and linear regressions offer high interpretability, allowing users to trace specific decisions back to individual features or conditions (Ajayi, et al., 2025: Oluokun, et a., 2025). On the other hand, complex deep learning models like LSTMs or Transformers often function as black boxes, offering little insight into internal decision-making processes. This lack of transparency can be problematic in high-stakes environments. As a result, evaluation of interpretability now often includes the use of explainability tools like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), or attention maps to extract human-readable insights from opaque models.

Comparing model types across deployment scenarios provides further understanding of their contextual suitability. Supervised machine learning models such as Random Forests and SVMs are known for their robustness and clarity in relatively structured environments, such as predicting traffic patterns in semi-static urban regions. They perform well when trained on well-labeled historical datasets and are preferred in scenarios where interpretability and low computational complexity are important (Attah, et al., 2024, Chintoh, et al., 2025: Oladipo, Dienagha & Digitemie, 2025). However, their performance may decline in highly dynamic or unstructured scenarios where user behavior or network topologies change rapidly.

Deep learning models like CNNs and LSTMs excel in these dynamic scenarios due to their ability to learn complex, non-linear relationships in large and evolving datasets. For instance, LSTMs are highly effective in modeling time-series data for predicting mobile user movement or real-time changes in network load. However, they may suffer from high inference latency and require substantial computational resources, making them less suitable for edge deployment or low-power environments unless optimized (Attah, et al., 2024, Chintoh, et al., 2024). Transformer-based models offer high accuracy and scalability but pose challenges in terms of model size and interpretability.

Bayesian and probabilistic models, although often less accurate than data-hungry deep learning methods, shine in uncertainty estimation and risk-aware decision-making. They are particularly valuable in safety-critical applications or scenarios with limited labeled data. Hybrid and ensemble models, which combine the strengths of multiple techniques, often provide superior performance across metrics but at the cost of increased model complexity and deployment overhead (Attah, et al., 2024, Chintoh, et al., 2024: Okuh, et al., 2025).

Another important dimension of evaluation lies in the trade-offs between real-time and batch prediction models. Real-time prediction models are designed to operate continuously, generating insights as new data streams into the system. These are crucial in scenarios requiring immediate adaptation, such as handover management, fault isolation, or adaptive QoS provisioning. However, real-time models must be optimized for speed and lightweight execution, which often involves simplifying model architectures or limiting feature sets (Alonge, et al., 2023,).

Batch prediction models, in contrast, operate on historical or aggregated data and are typically used for long-term planning, such as infrastructure deployment, capacity forecasting, or predictive maintenance scheduling. These models can afford higher computational overhead and longer inference times, allowing the use of more complex algorithms and larger datasets. However, their insights may not be applicable in rapidly changing environments, and their utility depends on the assumption that historical trends will continue into the future (Attah, et al., 2024, Chintoh, et al., 2024, Okolie, et al., 2025).

The choice between real-time and batch predictions is not binary but context-dependent. In many practical 6G applications, a hybrid approach is used, wherein batch models are employed for strategic planning and real-time models for operational adjustments. For example, a batch model might forecast network demand over the next quarter, informing base station deployment, while a real-time model manages dynamic bandwidth allocation on a per-second basis during peak usage periods (Ajayi, et al., 2025: Ogunwole, et al., 2025). Evaluating the interplay between these modes involves measuring latency, accuracy drift over time, model update frequency, and integration complexity.

In summary, the evaluation of predictive intelligence models for product-centric 6G network planning and optimization is a multidimensional task that must consider accuracy, latency, scalability, and interpretability, among other factors. Comparative analysis across different models and deployment scenarios reveals that no single approach is universally superior, and trade-offs between prediction modes must be balanced according to specific use case requirements (Afolabi & Akinsooto, 2023, Chintoh, et al., 2024). As 6G networks move toward greater autonomy and intelligence, continuous refinement of evaluation frameworks will be essential to guide the selection, deployment, and evolution of predictive systems that are not only high-performing but also transparent, adaptive, and contextually aware (Atadoga, et al., 2024, Chintoh, et al., 2025: Ogunsola, et al., 2025).

2.6. Challenges and Research Gaps

The deployment of predictive intelligence models in product-centric 6G network planning and optimization has introduced a new frontier in network automation, agility, and user-centricity. These models promise to enable proactive decision-making, enhance network efficiency, and personalize service delivery across a wide spectrum of applications. However, as the systematic review of current literature reveals, several critical challenges and research gaps remain (Augoye, et al., 2025: Ogunnowo, et al., 2025). These limitations span across multiple dimensions, including data sparsity and model generalization, computational complexity, the need for transparent and explainable AI, and a noticeable lack of vertical-specific predictive models tailored to the unique requirements of emerging 6G services. Addressing these gaps is essential to realizing the full potential of AI in 6G environments and ensuring that predictive models are robust, scalable, and aligned with real-world use cases (Afolabi, Chukwurah & Abieba, 2025, Chianumba, et al., 2021).

One of the most pervasive challenges is data sparsity, particularly in the early stages of 6G network development. Predictive models, especially those based on supervised and deep learning, rely heavily on large volumes of high-quality data to achieve accurate and reliable performance. Yet, many of the anticipated 6G scenarios—such as high-altitude platforms, holographic communications, and ultra-reliable low-latency applications—are still in their infancy or have limited real-world deployment, resulting in insufficient training data (Alozie, et al., 2025: Ogbuagu, et al., 2025). Even in existing networks, acquiring annotated datasets with sufficient diversity and granularity remains difficult due to proprietary restrictions, high labeling costs, and data privacy concerns.

This data sparsity not only affects the training of predictive models but also impacts their ability to generalize across varying environments. For example, a model trained on urban traffic patterns may perform poorly in rural areas due to vastly different mobility profiles and usage behaviors (Alonge, et al., 2023). Similarly, models developed using 5G datasets may fail to capture the unique characteristics of 6G, including higher-frequency spectrum behavior, novel radio access technologies, and multi-access edge computing scenarios. The issue of generalization becomes even more pronounced when attempting to apply models across different geographic, socio-economic, and regulatory contexts (Afolabi, Chukwurah & Abieba, 2025: Odionu, et al., 2025). Research in transfer learning and meta-learning provides promising directions, but practical implementations in multi-domain telecom environments remain limited and underexplored.

Another substantial obstacle is the inherent complexity and computational overhead of many predictive intelligence models. Deep learning architectures, such as Transformers and LSTMs, while powerful, often require substantial processing power, memory, and energy—resources that are not always available in real-time, edge-based, or energy-constrained environments. The computational burden becomes particularly problematic in scenarios requiring low latency and high reliability, such as autonomous vehicle coordination or remote robotic surgery, where milliseconds can determine the success or failure of a network operation (Alozie, et al., 2025: Kokogho, et al., 2025). As networks increasingly shift toward edge and distributed computing architectures, there is a pressing need for lightweight and computationally efficient models that can deliver accurate predictions without compromising performance.

Despite advances in model compression, quantization, and hardware acceleration, the trade-off between model complexity and execution efficiency remains a key concern. Many existing studies prioritize predictive accuracy while neglecting runtime constraints, power consumption, and deployment feasibility in real-world telecom settings (Atadoga, et al., 2024, Chianumba, et al., 2024, Kanu, et al., 2025). Moreover, most optimization techniques used in model training focus on general-purpose metrics without considering the unique operational constraints of telecom infrastructures, such as processing latency, dynamic resource availability, and mobility-induced fluctuations in connectivity. Future research must develop more context-aware model training and deployment strategies that balance performance with operational constraints and scalability requirements (Alonge, et al., 2024).

Equally important is the need for explainable AI (XAI) in telecom. As predictive models increasingly influence critical decisions in network management—such as fault detection, dynamic routing, and SLA enforcement—the ability to interpret and trust these decisions becomes paramount. Telecom operators, engineers, and regulators must understand the rationale behind a model's prediction to assess its validity, trace errors, and ensure compliance with safety and service-level standards. However, many of the most accurate models, particularly deep neural networks, operate as black boxes, offering limited transparency into their inner workings (Ariyibi, et al., 2024, Charles, et al., 2022).

The lack of explainability not only hinders operator trust but also complicates debugging, auditing, and regulatory approval, particularly in highly regulated sectors such as healthcare, finance, and public safety where 6G networks are expected to play a central role. Tools such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention visualization offer partial solutions but are often limited in scope or too computationally expensive for real-time application (Arinze, et al., 2024, Charles, et al., 2023, Kanu, et al., 2025). There is a pressing need for XAI frameworks specifically tailored to telecom, capable of providing concise, relevant, and actionable insights into predictive model behavior in live operational settings. Future research should also explore how explainability can be embedded into model design from the outset rather than retrofitted post hoc, allowing transparency to co-evolve with performance and scalability (Alonge, et al., 2024).

A further and often overlooked gap is the limited research on vertical-specific predictive models. While much of the current literature focuses on general network performance optimization, fault detection, and traffic forecasting, there is relatively little work dedicated to developing predictive intelligence tailored to specific vertical industries that 6G aims to support (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024, Ikemba, Akinsooto & Ogundipe, 2025). These verticals include autonomous transportation, smart manufacturing, eHealth, immersive media, and smart agriculture, each with distinct requirements, data characteristics, and performance constraints.

For instance, predictive models designed for eHealth must prioritize reliability, data privacy, and low latency, often under resource-constrained edge conditions. In contrast, models for smart agriculture might emphasize energy efficiency, spatial analytics, and long-term environmental forecasting. The heterogeneity of these domains demands specialized models that can incorporate domain knowledge, interface with industry-specific protocols, and deliver context-aware predictions (Alozie, et al., 2025: Igunma, Adeleke & Nwokediegwu, 2025). Yet, current research often treats these verticals as generic use cases rather than unique ecosystems requiring bespoke solutions. This one-size-fits-all approach limits the practical applicability and relevance of predictive intelligence in real-world 6G deployments.

Moreover, vertical-specific models require interdisciplinary collaboration between telecom engineers, AI researchers, and domain experts, which is often lacking in current research initiatives. This gap underscores the need for new research programs, funding mechanisms, and academic-industry partnerships that prioritize co-design and co-development of predictive models within the context of specific verticals. Benchmarks and open datasets relevant to these domains are also scarce, further hindering progress in this direction (Arinze, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024,).

In conclusion, while predictive intelligence models hold immense promise for enabling proactive, personalized, and autonomous 6G network planning, several challenges and research gaps must be addressed to fully unlock their potential. Data sparsity and limited generalization capabilities constrain model robustness and scalability, especially in emerging 6G environments. High computational overhead restricts real-time deployment, particularly in edge and resource-constrained settings. The lack of explainability undermines trust, operability, and regulatory compliance (Afolabi, Chukwurah & Abieba, 2025: Ibeh & Adegbola, 2025). Finally, the dearth of vertical-specific models limits the applicability of predictive intelligence in key sectors that 6G aims to transform. Bridging these gaps requires a multi-faceted research agenda that combines technical innovation with interdisciplinary collaboration, real-world validation, and a deeper understanding of the diverse contexts in which 6G networks will operate. Only then can predictive intelligence become a true enabler of the intelligent, adaptive, and user-centric networks envisioned for the future (Alonge, Dudu & Alao, 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024, Hassan, et al., 2025).

2.7. Future Research Directions

As the field of predictive intelligence for product-centric 6G network planning and optimization matures, the need for targeted, innovative, and scalable research becomes increasingly pressing. While significant progress has been made in developing and applying machine learning and AI-based models for network forecasting, fault detection, traffic prediction, and service optimization, emerging requirements driven by the unique characteristics of 6G networks demand new research directions (Adikwu, et al., 2025: Ibeh, et al., 2025). These include developing lightweight and energy-efficient predictive models, advancing federated and privacy-preserving learning frameworks, tightly integrating predictive intelligence with digital twins and network automation stacks, and enabling predictive orchestration in ultra-dense and cross-domain scenarios (Adewoyin, et al., 2025: Gbaraba, et al., 2025). These research directions are pivotal to building the intelligent, autonomous, and user-driven networks envisioned in the 6G era.

A key research challenge moving forward is the development of lightweight and energy-efficient predictive models suitable for real-time inference in decentralized environments. Unlike traditional centralized computing systems, 6G will heavily rely on distributed architectures such as mobile edge computing (MEC) and device-to-device networks, where computational power and energy resources are limited (Adewoyin, Adediwin & Audu, 2025, Alonge, Dudu & Alao, 2024). In these settings, deploying large-scale deep learning models, such as Transformers or deep convolutional networks, becomes impractical due to the prohibitive memory and processing demands (Abisoye, et al., 2025: Ezechi, et al., 2025). Future research must therefore focus on model compression, pruning, quantization, and knowledge distillation techniques to reduce the size and complexity of predictive models without significantly compromising accuracy (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024, Ezeanochie, Afolabi & Akinsooto, 2025).

Additionally, the design of novel neural network architectures specifically optimized for energy-constrained environments—such as spiking neural networks, binarized networks, or attention-sparse Transformers—can contribute significantly to this objective. These models must be capable of delivering high-speed predictions with minimal computational overhead to support tasks such as real-time handover management, localized fault prediction, or on-device QoS optimization. Moreover, lightweight models must be adaptive, able to self-update incrementally without retraining from scratch when network conditions evolve or service requirements change (Arinze, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023). The pursuit of efficient architectures will help ensure that predictive intelligence is scalable, sustainable, and accessible across all tiers of the 6G network hierarchy, from core networks to edge nodes and end-user devices.

Closely related to the need for computational efficiency is the growing demand for federated and privacy-preserving learning models. In 6G networks, massive volumes of data will be generated by billions of connected devices, many of which will be highly sensitive in nature—especially in domains such as eHealth, autonomous vehicles, or smart cities. Traditional approaches to centralized machine learning, which rely on aggregating raw data in a central server, pose significant privacy, security, and bandwidth challenges (Alonge, 2021). Federated learning (FL) offers a promising alternative by enabling collaborative model training across distributed devices without transferring raw data. Each device or node trains a local model using its own data and shares only model updates with a coordinating server for aggregation (Abisoye, et al., 2025, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024).

Future research should aim to enhance the scalability, robustness, and efficiency of federated learning in telecom contexts. One area of exploration involves improving communication efficiency, as the exchange of model gradients or parameters can itself become a bottleneck in bandwidth-constrained networks. Compression and sparsification techniques, along with asynchronous update schemes, can mitigate this problem (Alahira, et al., 2024). Another research need lies in addressing the statistical heterogeneity inherent in telecom data, where data distributions across nodes can be non-IID (independent and identically distributed) due to differences in user behavior, device types, or geographical conditions (Anyanwu, et al., 2024, Ezeanochie, Akinsooto & Ogunnowo, 2025). Personalized FL approaches, which allow for local model variations tailored to specific nodes while still benefiting from global learning, offer a potential solution.

In tandem with federated learning, privacy-preserving mechanisms such as differential privacy, secure multi-party computation, and homomorphic encryption must be integrated to provide mathematical guarantees about data confidentiality. As 6G networks begin to support critical infrastructure and services, the ethical and regulatory imperative for privacy by design will intensify, demanding models that are both performant and compliant with international data protection standards. Research in this area should not only focus on algorithmic development but also on real-world implementation feasibility, including system-level integration and trade-offs between privacy, utility, and latency (Alahira, et al., 2024).

The integration of predictive intelligence with digital twins and network automation stacks marks another frontier in 6G research. Digital twins—virtual replicas of physical network entities or environments—provide a powerful framework for simulating, analyzing, and optimizing network behavior in real time. When combined with predictive models, digital twins enable what-if analysis, proactive planning, and real-time decision support. For example, a digital twin of a metropolitan RAN (radio access network) can simulate the effects of anticipated traffic surges, environmental disruptions, or infrastructure upgrades, using predictive models to guide reconfiguration strategies before issues materialize (Anyanwu, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023).

Future research must address how to tightly couple predictive intelligence engines with digital twin environments to support continuous feedback loops, co-simulation, and co-optimization. This involves creating standardized interfaces for real-time data exchange, developing synchronization mechanisms to align virtual and physical states, and ensuring low-latency, high-fidelity simulation capabilities. Moreover, predictive models must be designed to update dynamically based on real-world feedback, enabling digital twins to evolve alongside the actual network (Abieba, Alozie & Ajayi, 2025: Ekeh, et al., 2025). The integration of network automation stacks—responsible for provisioning, orchestration, monitoring, and assurance—completes the loop by allowing predictions to trigger autonomous actions, such as rerouting, scaling, or healing.

Such closed-loop systems must also be interpretable, traceable, and auditable, especially in mission-critical domains. Research into explainable AI within this integrated framework is essential to ensure that the decisions made by predictive models and executed by automation systems can be justified and controlled. Collaboration between AI researchers, telecom engineers, and systems architects is vital to ensure that these multi-layered systems remain manageable, secure, and aligned with operational goals (Alabi, et al., 2024).

Finally, a crucial research direction lies in the development of predictive orchestration strategies for ultra-dense and cross-domain 6G scenarios. As 6G networks expand to accommodate trillions of devices and a growing diversity of services, orchestration will need to operate at unprecedented scale and granularity (Aminu, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2024). Predictive orchestration refers to the ability to forecast future network states—such as load, fault probability, or service demands—and proactively adapt network configurations, resource allocations, and policy enforcements. In ultra-dense environments, such as smart factories or urban IoT ecosystems, predictive orchestration can help avoid resource contention, interference, and bottlenecks before they degrade performance. Research is needed to develop orchestration algorithms that are not only predictive but also scalable, distributed, and context-aware. These algorithms must process inputs from multiple domains—radio, transport, compute, storage, and applications—and generate coherent control signals that span multiple network layers and operators. Cross-domain orchestration also requires semantic interoperability, standardized descriptors, and intent-based frameworks that translate high-level service requirements into actionable configurations. Predictive orchestration must also balance competing objectives such as energy efficiency, latency, reliability, and user fairness, which often exist in tension (Alabi, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Ekeh, et al., 2025).

Additionally, the orchestration layer must be resilient to model uncertainty and prediction errors. This calls for robust optimization techniques, feedback correction mechanisms, and model confidence scoring to ensure that decisions remain effective even in the face of incomplete or uncertain inputs. Incorporating reinforcement learning agents capable of learning optimal policies over time through interaction with the network environment may provide a solution, but such agents must be carefully trained and monitored to prevent unintended consequences.

In conclusion, the future research directions for predictive intelligence in product-centric 6G network planning and optimization are diverse, ambitious, and deeply intertwined with the technical, operational, and ethical challenges of next-generation networks. Developing lightweight and energy-efficient models will ensure that predictive systems can function effectively across decentralized, resource-constrained environments (Alabi, et al., 2024). Advancing federated and privacy-preserving learning frameworks will safeguard user data and enable collaborative intelligence across distributed devices. Integrating predictive intelligence with digital twins and automation stacks will create dynamic, real-time, and autonomous systems capable of adapting to complex scenarios (Aminu, et al., 2024, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Ekeh, et al., 2025). Lastly, enabling predictive orchestration in ultra-dense and cross-domain networks will ensure that 6G networks are not only intelligent but also responsive, efficient, and resilient at scale. Together, these research avenues will shape the foundation of intelligent and adaptive infrastructures that define the 6G era.

2.8. Conclusion

The systematic review of predictive intelligence models in product-centric 6G network planning and optimization has revealed a rapidly evolving research landscape, driven by the need for intelligent, anticipatory, and service-oriented network design. The findings underscore that a wide array of machine learning, deep learning, probabilistic, and hybrid models have been proposed and tested to address the unique demands of 6G environments—ranging from traffic prediction and handover optimization to QoS forecasting, fault detection, and dynamic resource allocation. These models are increasingly capable of leveraging diverse data sources, including historical traffic, geospatial context, device usage patterns, and digital twin simulations, to support proactive and autonomous decision-making across multiple network layers. Yet, the review also highlights critical gaps in current research, including challenges with data sparsity, generalizability, computational complexity, interpretability, and a lack of vertical-specific applications tailored to emerging 6G use cases.

The implications of these findings for 6G network design and policy are far-reaching. As 6G shifts toward a product-centric paradigm—characterized by personalized services, dynamic network slicing, and user-experience-driven architectures—predictive intelligence must be integrated not as a peripheral feature but as a central pillar of network infrastructure. For designers, this means embedding predictive capabilities within orchestration, control, and assurance layers from the ground up. For policymakers and regulators, the review points to the need for frameworks that address the ethical, privacy, and interoperability challenges posed by AI-driven decision-making in critical communications systems. Policies must ensure transparency, fairness, and accountability while fostering innovation through the standardization of data sharing, model validation, and deployment practices across stakeholders and vendors.

Ultimately, predictive intelligence emerges from this review not merely as a technological enhancement but as a strategic enabler of the autonomous, self-optimizing, and user-focused systems envisioned in 6G. Its capacity to learn from data, anticipate network dynamics, and adapt in real time transforms traditional static planning into a continuous, closed-loop process. As networks evolve to support an increasingly diverse and demanding digital society, predictive intelligence stands as a catalyst for unlocking the full potential of 6G—empowering networks to become not only faster and more efficient but also more responsive, resilient, and deeply aligned with the needs of the end user.

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