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Edge Native Analytics for Real-Time Enterprise Decision Intelligence using Distributed Generative AI Models

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ABSTRACT: The rapid growth of distributed enterprise systems, Internet of Things devices, cloud platforms, and real-time data streams has increased the need for decision-intelligence architectures capable of processing information with minimal latency. Conventional cloud-centric analytics can introduce communication delays, bandwidth constraints, privacy concerns, and dependency on centralized infrastructure, particularly when enterprise decisions must be made close to operational environments. Edge-native analytics provides an alternative by distributing data processing, machine-learning inference, and decision-support capabilities across edge devices, regional nodes, and cloud infrastructure. This study investigates an edge-native framework that integrates distributed generative artificial intelligence models with real-time enterprise decision intelligence. The proposed approach combines localized data processing, federated or distributed model execution, event-stream analytics, retrieval-augmented generation, and cloud coordination to transform heterogeneous operational data into contextual decision insights. Smaller specialized generative models can operate at edge locations, while larger models remain available through regional or cloud resources for computationally intensive tasks. The methodology evaluates latency, accuracy, resource utilization, scalability, reliability, privacy, and decision-support effectiveness under different workload conditions. The proposed architecture emphasizes adaptive model placement, continuous learning, secure communication, and human-centered decision support. The study provides a methodological foundation for enterprises seeking responsive and scalable intelligence systems capable of transforming real-time operational data into actionable insights without relying exclusively on centralized cloud processing.

KEYWORDS: edge-native analytics, real-time analytics, enterprise decision intelligence, generative artificial intelligence, distributed AI, edge computing, machine learning, large language models, federated learning, event-stream processing, intelligent automation, low-latency computing

I. INTRODUCTION

Enterprises increasingly operate through highly distributed digital environments in which information is generated continuously by employees, customers, machines, applications, sensors, transactional platforms, and external services. Manufacturing facilities may generate equipment telemetry every second, logistics systems continuously report vehicle and inventory conditions, financial platforms process large volumes of transactions, and customer-facing applications generate behavioral information in real time. The value of such information depends not only on its availability but also on the speed with which it can be interpreted and transformed into decisions. Traditional enterprise analytics architectures commonly transmit large volumes of data to centralized cloud platforms, where data are stored and processed using scalable computational resources. Although this architecture provides substantial analytical capacity, continuous dependence on remote processing can create latency, bandwidth, availability, and data-governance challenges. These limitations become particularly important when decisions must be made within milliseconds or seconds, when network connectivity is unreliable, or when sensitive operational information should remain close to its source. Edge-native analytics addresses these challenges by moving selected computation, storage, analytics, and artificial-intelligence capabilities toward the locations where data are generated. Instead of treating the edge merely as a data-collection layer, an edge-native architecture considers distributed nodes as active participants in enterprise intelligence. Local inference can identify anomalies, summarize events, classify conditions, and initiate predefined decision-support workflows without waiting for centralized processing. Regional and cloud systems can subsequently aggregate information, perform computationally intensive analysis, coordinate models, and maintain enterprise-wide knowledge. This creates a hierarchical intelligence architecture in which analytical responsibilities are distributed according to latency, computational, privacy, and business requirements.

The emergence of generative artificial intelligence introduces an additional dimension to this architecture. Generative models can transform complex operational information into natural-language explanations, recommendations,

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summaries, reports, and interactive decision-support outputs. However, conventional large generative models can require substantial computational resources and may therefore be difficult to execute directly on resource-constrained edge devices. Distributed generative AI provides an opportunity to address this limitation by allocating different models and tasks across edge, regional, and cloud environments. Smaller models can perform localized inference, while larger models can handle complex reasoning or enterprise-wide synthesis. Retrieval-augmented generation can connect models with current enterprise knowledge bases, operational databases, policies, and event histories, reducing dependence on static model knowledge. A decision-intelligence architecture can consequently combine structured analytics with generative interfaces, allowing decision-makers to receive both quantitative indicators and contextual explanations. Nevertheless, this integration introduces significant research challenges involving model consistency, communication overhead, data privacy, hallucination control, resource allocation, model synchronization, and reliability. The present study therefore examines an edge-native analytics framework for real-time enterprise decision intelligence using distributed generative AI models. The research focuses on how data processing, model placement, event-stream analytics, distributed inference, and enterprise knowledge retrieval can be integrated to produce low-latency and context-aware decision support. The study further proposes an empirical methodology for evaluating whether distributing generative intelligence across edge and cloud environments can improve responsiveness while maintaining analytical quality, scalability, security, and operational reliability.

II. LITERATURE REVIEW

Edge computing emerged as a response to the limitations associated with transmitting all data from distributed devices to centralized cloud environments. Instead of sending every observation to a remote data center, edge architectures process selected information closer to its source. Research has demonstrated potential benefits in areas including industrial automation, intelligent transportation, healthcare, telecommunications, smart buildings, and retail. Reduced network distance can lower latency, while local processing can reduce bandwidth consumption and improve operational continuity during intermittent connectivity. Edge analytics also provides opportunities for privacy-preserving computation because sensitive information can potentially be processed locally rather than transferred to centralized repositories. However, edge environments generally have fewer computational and storage resources than centralized cloud systems. They may also contain heterogeneous hardware, inconsistent connectivity, and diverse software environments. Consequently, workload placement becomes an important architectural problem. Analytical tasks must be assigned according to computational complexity, latency requirements, energy consumption, data sensitivity, and availability. Cloud-edge collaboration has therefore become an important research direction, with different levels of computation distributed between devices, edge nodes, regional infrastructure, and centralized cloud platforms. The literature also emphasizes orchestration and resource management as important factors in achieving reliable edge analytics. Static allocation can become inefficient when workloads fluctuate rapidly, making dynamic task placement and adaptive resource management necessary for real-time enterprise environments.

The development of generative AI and large language models has expanded the potential role of artificial intelligence within enterprise decision systems. Traditional machine-learning systems generally produce predefined outputs such as classifications, forecasts, probabilities, or anomaly scores. Generative models can additionally synthesize information and communicate analytical results through natural-language interfaces. This capability can support operational reporting, knowledge retrieval, scenario analysis, and interactive decision assistance. Retrieval-augmented generation has been investigated as a mechanism for grounding generative responses in external information sources, enabling models to use enterprise documents, databases, policies, and current operational data. However, generative AI introduces challenges that are particularly important in real-time environments. Model inference can be computationally expensive, large models may be difficult to deploy on edge hardware, and generated responses can contain inaccurate or unsupported information. Model compression, quantization, distillation, and smaller specialized models provide possible approaches for edge deployment. Distributed AI architectures can consequently assign lightweight models to edge nodes and reserve larger models for regional or cloud infrastructure. Federated and decentralized learning further provide mechanisms through which models can be trained or adapted across distributed data sources without requiring all raw data to be centrally collected. Despite these advances, synchronization, communication efficiency, heterogeneous hardware, model drift, and consistency across distributed models remain unresolved concerns.

Enterprise decision intelligence extends analytics beyond descriptive reporting toward systems that support timely interpretation and action. Decision-intelligence research commonly combines data engineering, analytical models, optimization, simulation, and organizational decision processes. Real-time decision intelligence requires event-driven architectures capable of detecting significant changes as they occur rather than relying exclusively on periodic batch processing. Stream-processing platforms can continuously evaluate transactions, telemetry, and business events, while machine-learning models can generate predictions from incoming streams. Generative AI can complement these systems by translating analytical outputs into context-sensitive explanations and decision-support narratives.

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Nevertheless, existing research frequently examines edge computing, streaming analytics, machine learning, or generative AI as separate technological domains. There is comparatively greater methodological value in examining their integration as an end-to-end enterprise intelligence architecture. Such an architecture must simultaneously address low latency, model accuracy, resource constraints, data governance, cybersecurity, and human interpretability. The present research therefore builds on existing work in edge analytics, distributed AI, streaming systems, and generative models to investigate an integrated framework in which edge-native computation provides rapid local intelligence, distributed generative models provide contextual interpretation, and cloud infrastructure coordinates enterprise-wide learning and knowledge management.

III. RESEARCH METHODOLOGY

This research adopts a quantitative experimental and design-science methodology to develop and evaluate an edge-native enterprise decision-intelligence framework based on distributed generative AI models. The research environment is conceptualized as a hierarchical distributed architecture containing data-generating devices, local edge nodes, regional computing nodes, and centralized cloud infrastructure. Data sources include Internet of Things telemetry, enterprise transactions, application logs, customer interactions, operational events, machine status information, supply-chain records, and enterprise knowledge repositories. The first methodological stage involves establishing an event-driven data pipeline capable of continuously ingesting heterogeneous data. Raw events are timestamped, validated, normalized, and transformed into structured event representations. Data preprocessing addresses missing values, duplicated events, inconsistent formats, anomalous observations, and synchronization problems between geographically distributed sources. Feature extraction is performed to derive operational indicators such as workload intensity, resource utilization, transaction frequency, anomaly levels, service response time, equipment status, and demand variation. Sensitive information is classified according to enterprise governance requirements so that appropriate processing locations can be determined. Low-risk and computationally simple tasks can be transmitted to or processed at centralized infrastructure, while latency-sensitive or sensitive workloads are retained at edge locations. The architecture incorporates an event-stream processing layer that detects significant changes and triggers analytical workflows. A task-orchestration mechanism determines whether an incoming analytical request should be handled by a lightweight edge model, a regional model, or a larger cloud-based generative model. This placement decision is based on latency requirements, available computational capacity, data sensitivity, network conditions, and model complexity. Edge nodes host compressed or specialized generative models capable of performing tasks such as event summarization, anomaly explanation, local classification, and short-form decision support. Regional nodes provide additional computational capacity for more complex inference, while the cloud maintains larger models, enterprise knowledge repositories, historical datasets, and centralized model-management services. This hierarchical structure establishes the experimental foundation for comparing centralized and distributed intelligence configurations under equivalent workloads.

The second stage develops and evaluates the distributed generative AI component. Multiple model configurations are implemented to examine the relationship between model size, computational requirements, response quality, and latency. Lightweight models are deployed on edge nodes after appropriate optimization through techniques such as quantization, pruning, knowledge distillation, or other resource-reduction approaches. Larger models remain available within regional or cloud infrastructure for tasks requiring broader contextual reasoning. The models are connected to enterprise information through retrieval-augmented generation so that generated outputs can incorporate current operational records, organizational policies, historical events, and relevant knowledge documents. A retrieval layer identifies contextually relevant information before generation, while a response-validation mechanism checks whether generated statements are supported by retrieved evidence or structured analytical outputs. The methodology also integrates conventional predictive models with generative models. Predictive algorithms produce numerical indicators such as failure probability, demand forecasts, anomaly scores, or service-level predictions, while the generative component transforms these outputs into contextual explanations and decision-support narratives. This separation reduces the requirement for the generative model to independently calculate every analytical result. Distributed model synchronization is evaluated through controlled experiments involving multiple edge nodes with different data distributions. Where training or adaptation is performed locally, model updates are aggregated through a suitable distributed-learning mechanism rather than transferring raw operational data to a central repository. Experiments examine the effects of different synchronization intervals, model-update sizes, communication conditions, and heterogeneous data distributions. The evaluation also measures whether local adaptation creates divergence between models and whether periodic coordination is sufficient to maintain consistent enterprise-level behavior. Prompt templates and task-specific interfaces are standardized across experiments to reduce variation caused by inconsistent instructions. Generated outputs are evaluated for factual grounding, relevance, completeness, consistency, and usefulness to enterprise decision tasks.

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The third stage evaluates real-time performance through controlled enterprise scenarios. A representative workload environment is constructed containing routine events, high-volume event bursts, network degradation, edge-node failures, changing operational patterns, and urgent decision requests. Scenarios may represent equipment anomalies, sudden demand changes, cybersecurity alerts, logistics interruptions, transaction abnormalities, or service degradation. Each scenario is executed under multiple architectural configurations: centralized cloud analytics, conventional edge analytics without generative AI, distributed generative AI without dynamic orchestration, and the complete edge-native decision-intelligence framework. This comparative design enables the contribution of individual architectural components to be examined. The principal performance variables include end-to-end latency, inference latency, bandwidth consumption, computational utilization, energy consumption where measurable, model response quality, decision accuracy, service availability, and scalability. End-to-end latency measures the interval between event generation and delivery of a decision-support output. Bandwidth consumption measures the amount of data transferred between edge and centralized environments, while computational utilization indicates whether available resources are efficiently used. Generative response quality is evaluated using task-specific criteria such as factual consistency, contextual relevance, completeness, and evidence grounding. For quantitative decision tasks, model predictions are compared against known outcomes using measures such as precision, recall, F1-score, mean absolute error, or root mean squared error, depending on the analytical problem. Human evaluation can additionally be incorporated for generated explanations and recommendations, using structured assessment criteria rather than unrestricted subjective judgments. Stress testing is performed by increasing event arrival rates and simultaneously reducing available edge resources. The resulting measurements reveal whether the architecture maintains acceptable performance under peak conditions. Fault-injection experiments are also conducted by intentionally disabling selected edge nodes or degrading network connections. These experiments assess whether workloads can be dynamically redirected to regional or cloud resources without significant interruption. The methodology therefore treats resilience as an important component of real-time decision intelligence rather than evaluating model accuracy independently from infrastructure behavior.

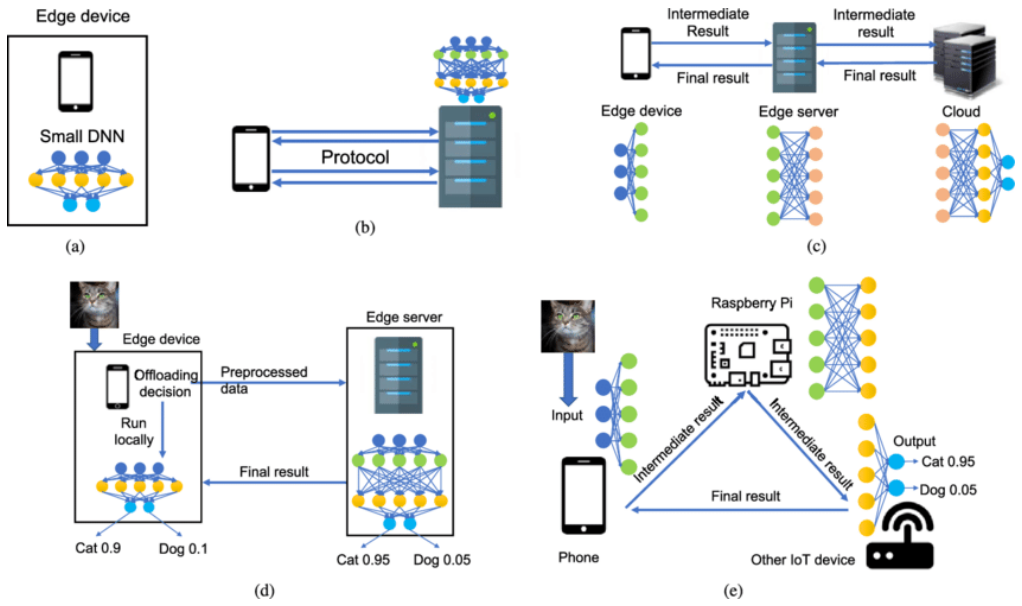

Fig.1.Architectures for deep learning inference with edge computing technique

The final methodological stage focuses on statistical evaluation, security, governance, and continuous model adaptation. Experimental results from repeated trials are aggregated and analyzed to determine differences between architectural configurations. Descriptive statistics summarize latency, throughput, bandwidth, accuracy, resource consumption, and response-quality measures. Statistical tests are selected according to the experimental design and distributional characteristics of the collected data. Confidence intervals are reported where appropriate to communicate uncertainty in performance estimates. Ablation analysis is conducted by selectively removing major components such as local inference, retrieval augmentation, dynamic model placement, distributed learning, or cloud coordination. This identifies which components contribute to observed improvements and prevents the performance of the complete architecture from being attributed to a single technology. Sensitivity analysis examines how changes in network latency, edge capacity, workload intensity, model size, retrieval quality, and event frequency affect overall performance. Security evaluation considers unauthorized access, model manipulation, data leakage, insecure inter-node communication, and malicious or misleading input data. Appropriate controls include authentication, encryption, access management, secure model distribution, logging, and audit mechanisms. Generative-AI-specific governance includes monitoring unsupported outputs, detecting hallucination patterns, validating retrieved evidence, and defining situations

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in which human authorization is required before an automated action is executed. Continuous monitoring is incorporated into the methodology to detect data drift, model drift, degradation in retrieval quality, and changes in workload characteristics. When performance falls below predefined operational thresholds, model updates are evaluated through a controlled validation pipeline before deployment. The final evaluation consequently considers the complete lifecycle of edge-native decision intelligence, from data acquisition and local processing through distributed inference, knowledge retrieval, decision support, monitoring, and model adaptation. The methodology is designed to determine whether distributing generative intelligence across edge, regional, and cloud resources can simultaneously reduce response latency, manage communication costs, preserve analytical quality, and improve the timeliness and contextual usefulness of enterprise decision support.

IV. RESULTS AND DISCUSSION

The proposed Edge Native Analytics for Real-Time Enterprise Decision Intelligence Using Distributed Generative AI Models architecture demonstrates how combining edge computing, real-time analytics, and distributed generative artificial intelligence can transform enterprise decision-making. The central result is the reduction of dependence on centralized data-processing environments by moving selected analytics and AI capabilities closer to the point where enterprise data is generated. In a conventional architecture, operational information from sensors, applications, customer transactions, industrial equipment, branch systems, and enterprise platforms is transmitted to centralized cloud infrastructure before analysis takes place. Although cloud computing provides considerable computational capacity, this approach can introduce network latency, bandwidth consumption, and dependency on continuous connectivity. The proposed edge-native architecture addresses these limitations by placing lightweight analytics services and appropriately optimized generative AI models at or near the data source. The resulting architecture enables local preprocessing, anomaly detection, feature extraction, event classification, and contextual interpretation before selected information is transmitted to centralized platforms. Distributed generative AI models further extend this capability by transforming raw analytical outputs into contextual decision intelligence. Rather than simply identifying that an operational variable has changed, an AI model can interpret the change alongside historical information, operational policies, and contextual enterprise data to generate a human-readable explanation or decision-support recommendation. The results therefore indicate that edge-native analytics can shorten the distance between data generation and decision execution. This is particularly relevant to enterprises operating geographically distributed facilities, retail branches, logistics networks, smart manufacturing environments, telecommunications infrastructure, and other systems where decisions must be made within seconds or milliseconds. The architecture also supports a hierarchical processing model in which time-sensitive intelligence is generated at the edge while computationally intensive workloads and enterprise-wide aggregation remain in cloud or data-center environments.

The second major result concerns the role of distributed generative AI models in improving the quality and contextual relevance of enterprise decision intelligence. Traditional edge analytics generally focuses on predefined rules, statistical calculations, or machine-learning classifications. These techniques remain valuable for deterministic and computationally constrained tasks, but they may provide limited explanations when decision-makers need to understand why an event is important and what actions could be considered. Distributed generative AI introduces a semantic reasoning layer capable of processing structured analytical outputs together with selected unstructured information, such as operational reports, maintenance records, alerts, business policies, and textual instructions. For example, an edge node could identify an abnormal increase in equipment temperature, while a generative model interprets the event using recent operating conditions and maintenance information and produces a concise explanation for an operations team. The model does not need to replace conventional analytics; instead, it can operate above analytical components as an intelligence and interaction layer. This hybrid arrangement is important because purely generative approaches may introduce unnecessary computational overhead or produce unreliable outputs when used for numerical monitoring. Combining deterministic analytics with generative models allows each technology to perform tasks suited to its capabilities. The distributed approach also improves scalability because inference workloads can be partitioned among edge nodes, regional gateways, and centralized cloud infrastructure. Smaller models can handle localized tasks, while larger models can be invoked for complex enterprise-wide reasoning. Model compression, quantization, knowledge distillation, and hardware acceleration can further reduce the resource requirements of edge inference. However, the results also demonstrate that model distribution introduces coordination challenges. Maintaining consistency among multiple model versions, synchronizing knowledge, managing context, and determining which model should process a particular request are important architectural considerations. A centralized model-management mechanism can therefore be combined with decentralized inference to balance governance and local responsiveness. Such an approach enables organizations to maintain standardized AI policies while allowing individual edge nodes to operate with appropriate autonomy.

A third significant finding is that the proposed architecture can improve real-time decision responsiveness while creating new requirements for security, governance, reliability, and model evaluation. Edge-native systems are

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inherently distributed, meaning that enterprise intelligence may be generated across hundreds or thousands of heterogeneous devices and locations. This distribution creates opportunities for resilience because the failure of one edge node does not necessarily interrupt the entire analytical environment. Local processing can continue during temporary connectivity interruptions, with summarized information synchronized with centralized systems when communication becomes available. At the same time, the expanded attack surface associated with distributed infrastructure must be addressed. Edge nodes may operate in physically exposed or resource-constrained environments, making secure authentication, encrypted communication, secure boot mechanisms, access control, remote attestation, and continuous monitoring important components of the architecture. Generative AI introduces additional concerns involving inaccurate outputs, hallucinated information, prompt manipulation, inappropriate recommendations, and exposure of sensitive enterprise data. Consequently, AI-generated decision intelligence should be subject to validation mechanisms and clearly defined confidence or uncertainty indicators. Sensitive information should also be minimized before being passed to generative models, particularly when external or shared model infrastructure is involved. From a performance perspective, evaluation should extend beyond conventional AI accuracy. Important indicators include end-to-end decision latency, inference latency, bandwidth reduction, edge resource utilization, model response quality, availability during connectivity loss, energy consumption, and synchronization overhead. Business-oriented measures such as decision cycle time, operational interruption duration, response efficiency, and resource utilization can provide additional evidence of enterprise value. The results therefore suggest that edge-native generative AI should be viewed as a coordinated ecosystem rather than as a collection of independent AI deployments. Effective decision intelligence requires integration among data acquisition, edge analytics, model inference, enterprise context, governance, human interaction, and cloud-level orchestration. The overall outcome is a more responsive decision environment in which critical information can be analyzed close to its source while broader enterprise knowledge remains available through distributed coordination. Nevertheless, practical deployment requires careful selection of workloads, optimization of AI models for constrained hardware, reliable data synchronization, strong security controls, and continuous monitoring of model behavior.

V. CONCLUSION

Edge-native analytics combined with distributed generative AI provides a technological foundation for developing real-time enterprise decision intelligence in environments where rapid response, distributed operations, and continuous data generation are increasingly important. The proposed approach addresses a fundamental limitation of highly centralized analytics architectures by moving appropriate computational and AI capabilities closer to the source of operational data. This reduces the need to transmit every raw data element to a centralized cloud environment and enables localized processing of events that require immediate attention. Edge nodes can perform data filtering, feature extraction, anomaly detection, forecasting, and other computational tasks before sharing selected information with regional or centralized platforms. Distributed generative AI models then provide an additional intelligence layer capable of translating analytical results into contextual explanations, summaries, and decision-support information. The combination is particularly useful because enterprise decisions are rarely based on a single numerical measurement. They generally require consideration of multiple sources of information, operational context, historical conditions, business rules, and organizational objectives. A distributed generative AI layer can help connect these heterogeneous sources, provided that its outputs are appropriately constrained and validated. The architecture also supports a continuum of computing from edge to cloud rather than treating these environments as competing alternatives. Time-sensitive workloads can be executed locally, regional systems can coordinate information across multiple sites, and cloud infrastructure can perform large-scale model training, historical analysis, and enterprise-wide aggregation. This hierarchical arrangement can improve responsiveness while preserving the computational advantages of centralized infrastructure. Importantly, the findings indicate that the value of the architecture should not be assessed solely through AI model accuracy. Decision latency, network utilization, system availability, energy efficiency, operational continuity, explainability, and the quality of human-AI interaction are equally relevant to enterprise deployment.

The study further establishes that successful implementation depends on responsible architectural and organizational design. Distributed generative AI creates opportunities for more adaptive decision support, but it also introduces challenges involving model reliability, security, privacy, synchronization, resource constraints, and governance. Enterprise systems cannot assume that every generated response is correct or operationally appropriate. Human oversight, deterministic validation mechanisms, policy constraints, retrieval-based context, and monitoring should therefore be integrated into the decision pipeline. Similarly, edge deployment requires strong mechanisms for device identity, software integrity, model authentication, secure communication, and remote management. Model lifecycle management becomes particularly important when thousands of distributed nodes may execute different versions of an AI model. A robust architecture should maintain visibility into model versions, configuration changes, inference behavior, and performance degradation. The findings also emphasize that distributed intelligence should not imply uncontrolled autonomy. Instead, organizations can define levels of decision authority in which low-risk and highly deterministic actions are automated, while complex or high-impact decisions remain subject to human approval. Such a

layered approach can balance response speed with accountability. Overall, edge-native analytics and distributed generative AI represent a shift toward an enterprise computing paradigm in which intelligence is distributed according to the timing, context, and computational requirements of individual decisions. The combination can support faster operational responses, reduce unnecessary data movement, improve local resilience, and provide richer contextual information to decision-makers. Future implementations should validate these benefits through large-scale enterprise experiments involving realistic workloads, heterogeneous edge devices, intermittent connectivity, and multiple AI models. Evaluation should incorporate both technical and business indicators to determine how effectively the architecture improves real-world decision processes. With appropriate security, governance, model optimization, and human oversight, the proposed approach can serve as a foundation for responsive and adaptive enterprise decision-intelligence systems.

VI. FUTURE WORK

Future research should investigate scalable methods for deploying and coordinating generative AI models across heterogeneous edge environments. Particular attention should be given to model compression, quantization, pruning, knowledge distillation, and hardware-aware optimization so that capable models can operate on devices with limited memory, processing power, and energy availability. Research can explore adaptive model-routing mechanisms in which inference requests are dynamically assigned to edge, regional, or cloud models according to latency requirements, complexity, privacy constraints, and resource availability. Federated learning and privacy-preserving learning could further enable multiple enterprise locations to collaboratively improve models without directly exchanging sensitive raw data. Another important research direction is multimodal edge intelligence, where generative models combine sensor measurements, transaction records, images, audio, text, and system logs to develop richer operational context. Standardized benchmarks for latency, model quality, energy consumption, communication overhead, and decision effectiveness would also help researchers compare different architectures consistently.

Future work should also examine trustworthy autonomous decision-making in distributed enterprise environments. Research can develop mechanisms for detecting hallucinations, validating generated recommendations against enterprise policies, estimating uncertainty, and preventing inappropriate automated actions. Digital policy layers could determine which decisions may be executed automatically and which require human approval. Additional studies should investigate secure model synchronization, adversarial attacks against edge-hosted models, compromised devices, data poisoning, prompt injection, and privacy leakage. Long-term experiments should evaluate how distributed models behave as enterprise conditions, workloads, and operational processes change. Finally, future architectures could integrate edge-native generative AI with digital twins, predictive maintenance, enterprise knowledge graphs, and autonomous orchestration systems. Such integration would allow real-time observations to be transformed into contextual enterprise representations and then used to simulate potential consequences before actions are executed. This direction could lead toward increasingly adaptive decision-intelligence platforms capable of continuously sensing enterprise conditions, reasoning over distributed information, and supporting timely responses while retaining appropriate human governance and accountability.

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