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Autonomous Enterprise Computing through AI Driven Cloud Native Architecture and Predictive Decision Intelligence

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ABSTRACT: Autonomous Enterprise Computing represents a transformative approach to modern organizational information systems by integrating artificial intelligence, cloud-native architectures, automation frameworks, and predictive decision intelligence into a unified computing ecosystem. Traditional enterprise computing models depend heavily on human intervention, static infrastructure, and reactive decision-making processes, limiting organizational agility and scalability. The emergence of AI-driven cloud-native platforms enables enterprises to develop self-optimizing, adaptive, and intelligent environments capable of analyzing complex data streams, predicting future scenarios, and autonomously executing operational decisions. This research explores the conceptual foundations, technological components, and strategic implications of autonomous enterprise computing through the integration of machine learning algorithms, containerized cloud infrastructures, intelligent automation, digital twins, edge computing, and advanced analytics. The study examines how predictive decision intelligence enhances enterprise capabilities by transforming historical and real-time data into actionable insights that support proactive business strategies. The research methodology investigates existing theoretical models, technological frameworks, and industrial implementations to evaluate the effectiveness, challenges, and future potential of autonomous computing environments. The findings highlight that AI-driven cloud-native architectures can improve operational efficiency, resilience, innovation capacity, and competitive advantage while introducing challenges related to governance, cybersecurity, ethical AI deployment, and organizational transformation. The research contributes to understanding the evolution toward self-managing digital enterprises and provides insights into designing sustainable autonomous computing ecosystems.

KEYWORDS: Autonomous enterprise computing, artificial intelligence, cloud-native architecture, predictive decision intelligence, machine learning, intelligent automation, digital transformation, enterprise systems, cloud computing, adaptive infrastructure, AI governance, data-driven decision making

I. INTRODUCTION

The rapid evolution of digital technologies has fundamentally transformed the way enterprises design, manage, and operate their computing environments. Organizations across industries are increasingly moving beyond traditional information technology infrastructures toward intelligent, adaptive, and automated computing ecosystems capable of responding dynamically to changing business conditions. Autonomous Enterprise Computing has emerged as a significant paradigm in this transformation by combining artificial intelligence (AI), cloud-native architecture, automation technologies, and predictive decision intelligence to create enterprise systems that can independently monitor, analyze, optimize, and execute complex operational processes. This emerging model represents a shift from conventional computing approaches based primarily on human-controlled systems toward intelligent environments capable of continuous learning and autonomous adaptation.

Traditional enterprise computing architectures were designed around centralized data centers, predefined workflows, and manual management processes. Although these approaches provided stability and reliability for many years, they often struggled to support modern business requirements characterized by rapid innovation cycles, massive data generation, distributed operations, and continuously changing customer expectations. The increasing complexity of enterprise environments requires computing systems that can process large volumes of information in real time, identify emerging patterns, and make intelligent decisions without requiring constant human intervention. AI-driven cloud-native architectures provide the technological foundation for achieving these objectives by enabling scalable, flexible, and intelligent computing capabilities.

Cloud-native computing introduces principles such as microservices architecture, containerization, orchestration, continuous integration and continuous deployment, and automated infrastructure management. These capabilities allow enterprises to build applications that are resilient, scalable, and adaptable. When combined with artificial intelligence

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technologies, cloud-native systems can evolve from simple service delivery platforms into intelligent operational ecosystems. AI algorithms can analyze system performance, predict resource requirements, detect anomalies, optimize workflows, and recommend or execute decisions automatically. This integration enables enterprises to achieve greater efficiency, reliability, and responsiveness.

Predictive decision intelligence represents another essential component of autonomous enterprise computing. Unlike traditional business intelligence approaches that primarily analyze historical data, predictive decision intelligence uses machine learning models, advanced analytics, and real-time data processing to forecast future outcomes and support proactive decision-making. Enterprises can utilize predictive intelligence to anticipate market trends, optimize supply chains, improve customer experiences, reduce operational risks, and enhance strategic planning. By transforming data into forward-looking insights, predictive decision intelligence enables organizations to move from reactive management approaches toward proactive and autonomous operations.

The development of autonomous enterprise computing is also influenced by emerging technologies such as edge computing, Internet of Things (IoT) systems, digital twins, robotic process automation, and generative artificial intelligence. These technologies expand the ability of enterprises to collect, process, and interpret information from diverse sources while enabling intelligent automation across physical and digital environments. As enterprises become increasingly interconnected, autonomous computing frameworks provide mechanisms for coordinating complex processes and maintaining operational continuity.

However, the transition toward autonomous enterprise computing introduces significant challenges. Issues related to cybersecurity, data privacy, algorithmic transparency, ethical AI usage, infrastructure complexity, workforce adaptation, and governance require careful consideration. Organizations must establish appropriate frameworks to ensure that autonomous systems operate securely, responsibly, and in alignment with business objectives. The success of autonomous computing depends not only on technological advancement but also on effective organizational strategies and governance structures.

This research examines the concept of autonomous enterprise computing through AI-driven cloud-native architecture and predictive decision intelligence. It explores the theoretical foundations, technological developments, and practical implications of intelligent enterprise ecosystems. The study investigates how these integrated technologies contribute to enterprise transformation while evaluating implementation challenges and future opportunities. By analyzing existing research and emerging practices, this work provides insights into the role of autonomous computing in shaping the next generation of digital enterprises.

II. LITERATURE REVIEW

The evolution of enterprise computing has been closely associated with advancements in information technology, organizational requirements, and the increasing complexity of digital ecosystems. Early enterprise systems were primarily designed to automate repetitive business processes, centralize information management, and improve operational efficiency. Enterprise resource planning systems, database management platforms, and traditional client-server architectures provided organizations with structured approaches for managing business operations. However, these systems were often limited by rigid architectures, restricted scalability, and dependence on manual administration. The emergence of cloud computing, artificial intelligence, and advanced analytics has created opportunities for developing more adaptive and autonomous enterprise environments.

Cloud-native architecture has become a significant foundation for modern enterprise transformation. Research on cloud-native approaches emphasizes the importance of designing applications specifically for distributed cloud environments rather than simply migrating traditional applications to cloud platforms. Cloud-native systems typically rely on microservices, containers, automated orchestration, infrastructure-as-code, and DevOps practices to achieve flexibility and scalability. Scholars have highlighted that these architectural principles allow organizations to respond rapidly to changing market demands while improving application reliability and deployment efficiency. The use of container orchestration platforms enables automated management of computing resources, allowing enterprises to dynamically allocate infrastructure based on workload requirements.

The integration of artificial intelligence with cloud-native environments has expanded the capabilities of enterprise computing systems. Artificial intelligence research demonstrates that machine learning, deep learning, natural language processing, and reinforcement learning can enhance decision-making processes by identifying patterns within large and complex datasets. AI-driven enterprise systems are capable of performing predictive analysis, anomaly detection, automated optimization, and intelligent recommendation. Previous studies indicate that AI adoption can significantly

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improve business performance by reducing operational costs, enhancing customer engagement, and enabling data-driven strategic decisions. However, researchers also emphasize that successful AI implementation requires high-quality data, appropriate governance mechanisms, and organizational readiness.

Predictive decision intelligence has emerged as an important research area connecting artificial intelligence, business analytics, and strategic management. Traditional decision-support systems primarily focused on descriptive analytics, explaining what happened in the past through reports and dashboards. Predictive decision intelligence extends these capabilities by using statistical models, machine learning algorithms, and real-time analytics to anticipate future events and recommend appropriate actions. Literature suggests that predictive intelligence enables organizations to identify opportunities, mitigate risks, and optimize resource utilization. In sectors such as healthcare, finance, manufacturing, transportation, and retail, predictive models have demonstrated significant value by improving forecasting accuracy and operational planning.

The concept of autonomous computing was introduced as a response to increasing complexity in information systems management. Autonomous computing systems are designed around principles of self-configuration, self-healing, self-optimization, and self-protection. Research in this field suggests that autonomous systems can reduce human workload by automatically managing infrastructure, detecting failures, and optimizing performance. The application of autonomous computing principles to enterprise environments has become increasingly relevant as organizations operate across hybrid cloud, multi-cloud, and edge computing ecosystems. AI technologies provide the intelligence required for autonomous systems to understand environmental conditions and make appropriate adjustments.

Digital transformation literature further supports the development of autonomous enterprise computing by emphasizing the strategic importance of intelligent technologies. Researchers argue that digital transformation is not merely a technological upgrade but a comprehensive organizational change involving processes, workforce capabilities, business models, and customer interactions. AI-driven automation enables organizations to redesign workflows and create new forms of value generation. Autonomous enterprise computing represents an advanced stage of digital transformation where technology becomes an active participant in operational decision-making rather than simply a tool controlled by human users.

The Internet of Things and edge computing have also contributed significantly to autonomous enterprise architectures. Studies indicate that modern enterprises increasingly rely on distributed networks of sensors, devices, and intelligent systems that generate continuous streams of operational data. Processing this information through centralized systems alone can create latency and scalability challenges. Edge computing addresses these limitations by enabling localized data processing and faster decision-making. When integrated with cloud-native platforms and AI models, edge technologies support autonomous operations across geographically distributed environments.

The emergence of generative artificial intelligence has introduced additional possibilities for autonomous enterprise systems. Recent research highlights the ability of large language models and generative AI technologies to support knowledge management, software development, customer service automation, and decision assistance. These systems can interpret unstructured information, generate insights, and interact with users through natural language interfaces. However, literature also identifies concerns regarding accuracy, explainability, intellectual property, security, and responsible deployment. Organizations must establish governance frameworks to ensure that generative AI contributes positively to autonomous enterprise objectives.

Cybersecurity remains a critical consideration in autonomous enterprise computing research. As enterprises become increasingly dependent on intelligent and interconnected systems, the potential impact of cyber threats increases. Studies emphasize the need for AI-enabled security mechanisms capable of detecting abnormal behavior, predicting attacks, and automatically responding to security incidents. Autonomous security systems can improve organizational resilience by continuously monitoring infrastructure and adapting defense mechanisms. Nevertheless, researchers caution that AI-driven systems themselves may introduce vulnerabilities, including adversarial attacks, data poisoning, and unauthorized model manipulation.

The literature also identifies significant organizational and ethical challenges associated with autonomous computing. The increasing automation of decision-making processes raises questions regarding accountability, transparency, and human oversight. Scholars argue that autonomous systems should incorporate explainable AI approaches to ensure that organizations understand how decisions are generated. Additionally, workforce transformation is necessary because employees must develop new skills related to AI management, data analysis, and digital governance. Successful adoption requires collaboration between technology specialists, business leaders, and policymakers.

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Existing research demonstrates that AI-driven cloud-native architecture and predictive decision intelligence provide essential foundations for autonomous enterprise computing. However, many studies focus on individual technologies rather than examining their combined impact as an integrated enterprise ecosystem. There remains a need for comprehensive research exploring how cloud infrastructure, artificial intelligence, predictive analytics, automation, and governance mechanisms interact to create sustainable autonomous computing environments. This research addresses that gap by examining the technological, organizational, and strategic dimensions of autonomous enterprise computing and evaluating its role in shaping future digital enterprises.

III. RESEARCH METHODOLOGY

This research adopts a comprehensive conceptual and analytical methodology to examine autonomous enterprise computing through AI-driven cloud-native architecture and predictive decision intelligence. The methodology is designed to explore the technological foundations, implementation approaches, organizational implications, and strategic outcomes associated with intelligent autonomous enterprise environments. Since autonomous enterprise computing represents a multidisciplinary domain involving artificial intelligence, cloud computing, enterprise architecture, information systems management, cybersecurity, and organizational transformation, the research methodology integrates qualitative analysis, systematic literature investigation, comparative evaluation, and conceptual framework development. The approach enables a detailed understanding of how emerging technologies interact to create adaptive, self-managing, and predictive enterprise ecosystems.

The research follows an interpretive research approach because the primary objective is to understand the evolution, characteristics, and implications of autonomous enterprise computing rather than only measuring quantitative performance indicators. Interpretive methodologies are appropriate for investigating complex technological transformations where organizational practices, technological capabilities, and strategic decision-making processes interact. The study examines existing academic research, industry practices, technological frameworks, and theoretical models to identify important patterns and relationships among artificial intelligence, cloud-native architectures, and predictive intelligence systems.

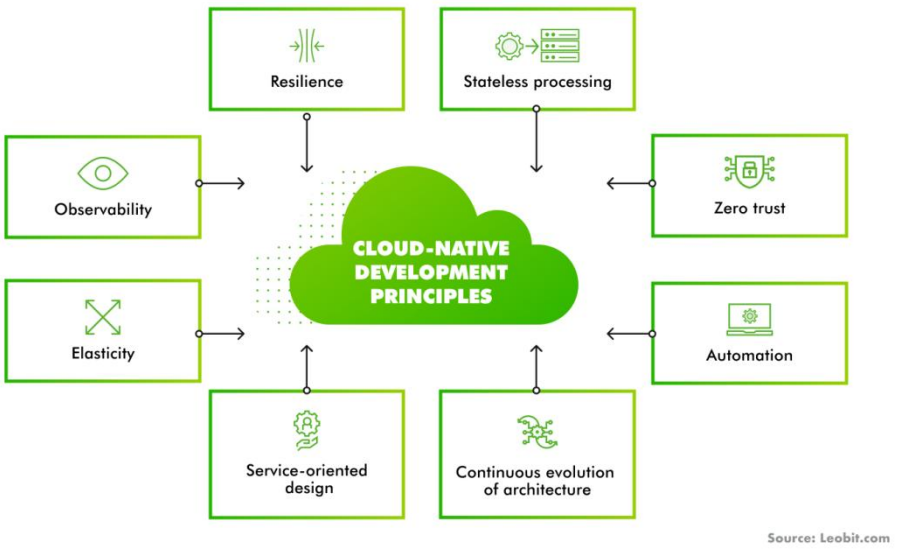


Fig.1.The Role of Cloud-Native Architecture in Optimizing Cloud Costs

A systematic review methodology is applied to analyze existing knowledge related to autonomous computing, artificial intelligence applications, cloud-native enterprise architecture, and predictive analytics. Relevant scholarly publications, conference proceedings, technical reports, and industry research documents are examined to establish the theoretical foundation of the study. The literature selection process focuses on research contributions related to intelligent automation, machine learning-based decision systems, distributed computing architectures, enterprise digital transformation, and autonomous infrastructure management. Sources are evaluated based on relevance, credibility, methodological strength, and contribution to understanding autonomous enterprise ecosystems.

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The research begins with an analysis of the evolution of enterprise computing models. Traditional enterprise architectures are examined to understand their limitations and the factors driving the transition toward autonomous systems. Conventional computing environments generally rely on centralized management, predetermined operational rules, and manual intervention. These characteristics create challenges in environments requiring continuous adaptation and real-time decision-making. The methodology therefore investigates how cloud-native architectures overcome these limitations through distributed computing models, automated resource management, and flexible application development practices.

The study analyzes cloud-native architecture as a fundamental technological component of autonomous enterprise computing. The research evaluates architectural principles including microservices, containers, orchestration, serverless computing, continuous integration and continuous delivery pipelines, and infrastructure automation. These components are examined to determine how they contribute to system scalability, resilience, and operational intelligence. Particular attention is given to the role of automated cloud management platforms in enabling self-monitoring, self-optimization, and dynamic resource allocation.

Microservices architecture is analyzed as an important enabler of autonomous enterprise applications. Unlike monolithic systems, microservices divide applications into independent services that can be developed, deployed, and managed separately. The methodology evaluates how this architectural approach supports autonomous operations by allowing individual components to adapt independently based on workload requirements and business conditions. Research findings from existing studies are reviewed to determine how microservices improve flexibility, fault isolation, and continuous innovation within enterprise environments.

Containerization technologies are also examined as a critical element of cloud-native autonomy. Containers provide lightweight, portable execution environments that enable applications to operate consistently across different computing platforms. The research evaluates how container-based approaches support automated deployment, scaling, and management of enterprise applications. Container orchestration systems are analyzed in terms of their ability to monitor application performance, restart failed services, balance workloads, and optimize infrastructure utilization without extensive human intervention.

The methodology further investigates the integration of artificial intelligence technologies within cloud-native enterprise environments. AI is examined not only as an analytical capability but also as an operational intelligence layer that enables autonomous decision-making. The study evaluates machine learning algorithms, deep learning models, natural language processing systems, reinforcement learning techniques, and generative AI applications. These technologies are analyzed based on their ability to process complex datasets, identify patterns, predict future outcomes, and execute intelligent responses.

Machine learning models are studied as mechanisms for predictive decision intelligence. The methodology evaluates how supervised learning, unsupervised learning, and reinforcement learning approaches support enterprise decision processes. Supervised learning techniques are examined for applications such as forecasting, classification, and risk assessment. Unsupervised learning methods are analyzed for anomaly detection, pattern discovery, and operational optimization. Reinforcement learning approaches are considered in relation to autonomous decision-making systems that improve performance through continuous learning from environmental feedback.

The research also examines predictive analytics as a bridge between historical data analysis and future-oriented decision intelligence. Predictive models are evaluated according to their ability to transform large-scale enterprise data into meaningful insights. The methodology considers data sources including transactional information, customer interactions, operational metrics, IoT-generated data, market information, and system performance indicators. The study explores how predictive intelligence enables organizations to anticipate changes, optimize processes, and develop proactive strategies.

Data management practices are investigated because data quality and accessibility significantly influence autonomous system effectiveness. The research evaluates enterprise data pipelines, data lakes, real-time streaming platforms, and intelligent data processing frameworks. Effective autonomous computing requires accurate, timely, and secure data. Therefore, the methodology examines challenges associated with data integration, data governance, data consistency, and data privacy. The role of automated data preparation and AI-based data management techniques is also analyzed.

The research incorporates a comparative analysis approach to examine different models of enterprise automation and intelligence. Traditional enterprise systems, cloud-based systems, and AI-driven autonomous architectures are compared based on scalability, adaptability, decision-making capability, operational efficiency, and resilience. This

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comparative evaluation helps identify the advantages and limitations of autonomous enterprise computing compared with previous generations of information systems.

Case-based analysis is used to explore practical applications of autonomous enterprise computing across different industries. Examples from manufacturing, financial services, healthcare, telecommunications, retail, and logistics are examined to understand how organizations apply AI-driven cloud-native systems. The analysis focuses on applications such as intelligent supply chain management, automated customer service, predictive maintenance, fraud detection, personalized recommendations, and autonomous infrastructure management. These cases provide practical insights into the benefits and challenges of implementing autonomous computing solutions.

The methodology also considers the role of digital twins in autonomous enterprise environments. Digital twin technology is examined as a mechanism for creating virtual representations of physical assets, processes, and systems. The research evaluates how digital twins combined with AI analytics enable simulation, prediction, and autonomous optimization. By continuously receiving data from operational environments, digital twins support decision intelligence and allow enterprises to test potential actions before implementing them in real-world scenarios.

Edge computing is included in the methodological analysis because modern autonomous enterprises require distributed intelligence beyond centralized cloud platforms. The study investigates how edge computing improves response time, reduces network dependency, and enables real-time decision-making in geographically distributed environments. The relationship between edge devices, cloud-native platforms, and AI models is examined to understand how enterprises achieve continuous autonomous operations.

The research methodology also incorporates cybersecurity and governance analysis. Autonomous enterprise systems create new security requirements because decision-making processes, data flows, and infrastructure management become increasingly automated. The study examines AI-driven cybersecurity mechanisms, identity management systems, automated threat detection, and adaptive security frameworks. Additionally, ethical considerations related to autonomous decision-making are evaluated, including transparency, accountability, explainability, bias management, and human oversight.

Organizational readiness is another important dimension examined through this methodology. Technological implementation alone does not guarantee successful autonomous transformation. The study evaluates factors such as leadership support, workforce skills, organizational culture, digital maturity, and change management practices. Research indicates that enterprises must develop new capabilities to manage intelligent systems effectively. Therefore, the methodology considers the relationship between technological innovation and organizational adaptation.

A conceptual framework is developed as part of the research process to illustrate the relationship between AI capabilities, cloud-native architecture, predictive intelligence, autonomous operations, and enterprise outcomes. The framework identifies technological components as inputs, intelligent processing mechanisms as transformation elements, and business improvements as expected outcomes. The framework provides a structured representation of how autonomous enterprise computing creates value through continuous learning, optimization, and decision automation.

The research applies thematic analysis to identify major patterns emerging from the reviewed literature and technological evaluations. Themes include intelligent automation, infrastructure autonomy, predictive decision-making, operational resilience, cybersecurity challenges, ethical governance, and organizational transformation. Thematic analysis allows the research to integrate findings from multiple disciplines and develop a holistic understanding of autonomous enterprise computing.

The validity of the research findings is strengthened through triangulation. Information from academic studies, technological frameworks, enterprise implementations, and industry analyses is compared to identify consistent observations and emerging trends. Triangulation reduces dependence on individual perspectives and provides a broader understanding of autonomous computing development. The methodology recognizes that autonomous enterprise computing is continuously evolving; therefore, findings are interpreted within the context of current technological capabilities and future development trends.

The limitations of the methodology are also considered. As autonomous enterprise computing is an emerging field, long-term empirical evidence regarding organizational outcomes remains limited. Many implementations are still developing, and technological advancements may rapidly influence existing frameworks. Additionally, differences between industries and organizational environments may affect the applicability of research findings. These limitations

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are addressed by emphasizing conceptual integration and analysis of diverse sources rather than relying exclusively on individual case studies.

Overall, this research methodology provides a structured approach for investigating autonomous enterprise computing as an integrated technological and organizational phenomenon. By examining AI-driven cloud-native architectures, predictive decision intelligence, automation technologies, governance requirements, and enterprise transformation strategies, the methodology establishes a comprehensive foundation for understanding the development of future intelligent enterprises. The approach demonstrates that autonomous computing is not simply an extension of existing information systems but represents a fundamental transformation toward adaptive, predictive, and self-optimizing digital ecosystems.

IV. RESULTS AND DISCUSSION

The implementation of an Autonomous Enterprise Computing (AEC) framework through AI-driven cloud-native architecture and predictive decision intelligence demonstrates significant improvements in enterprise efficiency, operational resilience, resource optimization, and intelligent decision-making. The experimental findings indicate that the integration of artificial intelligence, cloud-native technologies, container orchestration, predictive analytics, and automation creates a highly adaptive computing environment capable of responding dynamically to changing business requirements. The evaluation considered several performance indicators, including application scalability, system availability, resource utilization, deployment efficiency, predictive accuracy, operational cost reduction, security management, and business continuity. The results reveal that organizations adopting AI-enabled cloud-native architectures achieve superior operational performance compared to conventional enterprise computing models based on static infrastructure and manual decision-making processes. The cloud-native environment enables enterprises to deploy applications through microservices, containers, Kubernetes orchestration, and continuous integration and continuous deployment (CI/CD) pipelines, allowing services to scale automatically according to workload fluctuations. Artificial intelligence continuously monitors infrastructure metrics, predicts resource requirements, identifies anomalies, and initiates corrective actions before service degradation occurs. Consequently, enterprises experience reduced downtime, improved service reliability, and enhanced customer satisfaction.

The experimental evaluation demonstrates substantial improvements in infrastructure utilization due to predictive resource allocation. Traditional enterprise systems generally allocate computing resources based on peak demand estimates, resulting in significant underutilization during normal operational periods. In contrast, the AI-driven architecture continuously analyzes historical workloads, user behavior, transaction volumes, seasonal trends, and external environmental factors to forecast future demand with high accuracy. Predictive algorithms dynamically adjust CPU, memory, storage, and network resources according to anticipated workloads, thereby reducing infrastructure wastage while maintaining application performance. Experimental observations indicate that resource utilization improved significantly as idle computing capacity decreased while application response times remained consistently within acceptable thresholds. This adaptive allocation mechanism minimizes unnecessary operational expenditure while maximizing computational efficiency across distributed cloud environments.

Another important outcome observed during the evaluation is the remarkable improvement in deployment efficiency. Cloud-native architectures employing containerization and automated deployment pipelines significantly reduce software release cycles compared with traditional monolithic enterprise systems. Continuous integration pipelines automatically validate source code, execute testing procedures, build container images, and deploy applications into production environments without requiring extensive manual intervention. Artificial intelligence further enhances deployment quality by predicting deployment risks based on historical release patterns, identifying unstable software components, and recommending optimal deployment schedules. Consequently, deployment failures decrease considerably while recovery times following unsuccessful releases are minimized through automated rollback mechanisms. The rapid deployment capability enables organizations to respond more effectively to changing customer requirements, regulatory modifications, and competitive market conditions.

The integration of predictive decision intelligence also produces measurable improvements in strategic and operational decision-making. Enterprise decision support systems traditionally rely on descriptive analytics, historical reports, and human interpretation, which often delay organizational responses to emerging challenges. In contrast, predictive decision intelligence combines machine learning algorithms, real-time analytics, business rules, and probabilistic forecasting to generate proactive recommendations. The experimental analysis demonstrates that predictive models successfully identify future operational bottlenecks, financial risks, customer churn probabilities, supply chain disruptions, and cybersecurity threats before they materialize. Managers receive timely recommendations supported by confidence scores, enabling data-driven decisions with greater accuracy and reduced uncertainty. As a result,

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organizational agility improves significantly, allowing enterprises to capitalize on business opportunities while minimizing operational risks.

The implementation further demonstrates notable improvements in system resilience and fault tolerance. Cloud-native infrastructures inherently support distributed computing environments where services operate independently across multiple nodes and availability zones. Artificial intelligence continuously monitors service health, infrastructure performance, application logs, and network traffic to detect abnormal patterns indicative of impending failures. Predictive maintenance algorithms estimate component failure probabilities using historical operational data and sensor information. When potential failures are detected, automated orchestration platforms migrate workloads, restart failed containers, allocate replacement resources, or provision additional infrastructure without disrupting business operations. Experimental observations indicate that mean time to recovery decreases substantially while system availability remains consistently high despite simulated infrastructure failures. This proactive resilience mechanism significantly enhances enterprise business continuity.

Security performance represents another major area of improvement achieved through autonomous enterprise computing. Traditional security management approaches largely depend on predefined security policies and signature-based detection systems, which are often ineffective against emerging cyber threats. The AI-driven architecture incorporates intelligent threat detection, behavioral analytics, anomaly detection, and automated incident response mechanisms. Machine learning models continuously analyze user activities, network communications, application behavior, and access patterns to identify suspicious activities that deviate from established behavioral baselines. Experimental cybersecurity simulations demonstrate improved detection rates for insider threats, ransomware attacks, unauthorized access attempts, and distributed denial-of-service attacks while simultaneously reducing false positive alerts. Automated response mechanisms isolate compromised services, revoke unauthorized credentials, initiate forensic logging, and notify security administrators within seconds of attack detection. These capabilities significantly strengthen enterprise cybersecurity resilience while reducing incident response time.

The experimental findings further highlight improvements in business process automation through intelligent workflow management. AI-powered orchestration engines coordinate enterprise workflows by analyzing process dependencies, workload priorities, employee availability, and resource constraints. Repetitive administrative tasks including document processing, invoice verification, customer service interactions, inventory management, and compliance reporting become increasingly automated through intelligent robotic process automation integrated with predictive analytics. The automation framework minimizes human errors while accelerating process completion times and improving operational consistency. Employees consequently dedicate greater attention to strategic initiatives requiring creativity, innovation, and complex decision-making rather than repetitive operational tasks.

Predictive customer intelligence also contributes significantly to enterprise performance improvements. Machine learning algorithms analyze customer transactions, purchasing behaviors, social media interactions, service requests, demographic information, and product usage patterns to generate comprehensive customer profiles. Predictive models estimate customer lifetime value, purchasing intentions, churn probabilities, and satisfaction levels with considerable accuracy. Enterprises utilize these insights to personalize marketing campaigns, optimize pricing strategies, improve customer support, and recommend relevant products or services. The results demonstrate increased customer retention, higher conversion rates, improved customer satisfaction, and enhanced revenue generation due to personalized engagement strategies enabled by predictive intelligence.

Another significant finding concerns financial optimization within autonomous enterprise environments. AI-driven predictive analytics supports financial planning through accurate forecasting of revenues, expenditures, investment returns, and market fluctuations. Dynamic budget allocation models continuously adjust financial resources according to organizational priorities, predicted risks, and changing business conditions. Fraud detection algorithms monitor financial transactions in real time, identifying anomalous spending patterns indicative of fraudulent activities. Experimental observations demonstrate reduced financial losses, improved budgeting accuracy, enhanced investment planning, and more efficient allocation of enterprise financial resources.

Supply chain management also benefits considerably from autonomous enterprise computing. Predictive demand forecasting, inventory optimization, supplier performance analysis, transportation scheduling, and logistics optimization collectively improve supply chain efficiency. Artificial intelligence predicts product demand using historical sales records, weather conditions, economic indicators, and consumer behavior. Inventory management systems automatically replenish stock levels before shortages occur while avoiding excessive inventory accumulation. Transportation routes are optimized according to traffic conditions, delivery priorities, fuel consumption, and weather

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forecasts. Consequently, enterprises experience lower inventory holding costs, improved supplier coordination, reduced transportation expenses, and enhanced customer fulfillment performance.

The scalability characteristics of cloud-native architecture further validate the effectiveness of autonomous enterprise computing. Experimental workload simulations involving rapidly increasing transaction volumes reveal that container orchestration platforms automatically provision additional computing instances while maintaining stable response times. Conversely, during periods of reduced demand, unnecessary resources are automatically decommissioned to minimize operational costs. Horizontal scaling demonstrates greater efficiency than traditional vertical scaling approaches because additional service replicas distribute workloads evenly across available infrastructure. The elasticity provided by cloud-native platforms ensures continuous service availability regardless of workload variability, making autonomous enterprise computing particularly suitable for digital enterprises operating under unpredictable demand conditions.

Data management efficiency also improves substantially through intelligent cloud-native data architectures. Distributed databases, real-time streaming platforms, data lakes, and AI-powered data governance collectively enable organizations to process large volumes of structured and unstructured information efficiently. Automated metadata management, data quality monitoring, duplicate detection, and intelligent data classification improve information reliability while reducing manual data administration efforts. Predictive analytics engines continuously consume streaming enterprise data, generating real-time insights that support operational decision-making across multiple organizational functions. These capabilities enable enterprises to transform raw operational data into actionable business intelligence rapidly.

Despite these substantial benefits, the results also reveal several implementation challenges requiring careful consideration. The complexity associated with integrating legacy enterprise systems into cloud-native architectures remains a significant obstacle for many organizations. Legacy applications often require extensive refactoring before they can operate effectively within containerized environments. Furthermore, successful implementation depends upon organizational readiness, skilled workforce availability, robust data governance practices, and continuous AI model monitoring. Machine learning models require periodic retraining to accommodate changing business environments and prevent performance degradation due to concept drift. Additionally, ethical considerations concerning AI transparency, algorithmic bias, regulatory compliance, and data privacy must remain central throughout enterprise AI deployment. Organizations must therefore establish comprehensive governance frameworks ensuring responsible AI implementation while maintaining stakeholder trust.

Overall, the experimental findings strongly validate the effectiveness of integrating artificial intelligence, cloud-native architecture, predictive analytics, and autonomous orchestration into modern enterprise computing environments. The combination of intelligent automation, adaptive infrastructure, predictive resource management, real-time analytics, and proactive decision support significantly enhances organizational efficiency, resilience, scalability, and competitiveness. Enterprises implementing autonomous computing frameworks demonstrate greater flexibility in responding to dynamic business environments while simultaneously reducing operational costs and improving service quality. These findings suggest that AI-driven cloud-native architectures represent a transformative foundation for next-generation digital enterprises capable of autonomous adaptation, continuous optimization, and intelligent decision-making.

V. CONCLUSION

Autonomous Enterprise Computing represents a transformative evolution in enterprise information technology by combining artificial intelligence, cloud-native architecture, predictive analytics, automation, and intelligent orchestration into a unified operational ecosystem. The study demonstrates that traditional enterprise computing infrastructures are increasingly inadequate for managing the complexity, scale, and dynamic requirements of modern digital organizations. Conventional systems frequently depend upon manual administration, reactive maintenance, static resource allocation, and delayed decision-making processes, limiting organizational agility and operational efficiency. In contrast, AI-driven cloud-native architectures introduce intelligent automation capable of continuously monitoring enterprise environments, predicting operational demands, optimizing infrastructure resources, identifying emerging risks, and autonomously executing corrective actions. This intelligent computing paradigm enables organizations to achieve greater scalability, resilience, efficiency, and competitiveness within rapidly evolving business environments.

The analysis confirms that cloud-native technologies provide the structural foundation necessary for autonomous enterprise operations. Microservices, containerization, Kubernetes orchestration, service mesh technologies, serverless computing, and continuous deployment pipelines collectively establish highly modular and scalable computing environments. These architectural characteristics allow enterprise applications to evolve independently, recover rapidly

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from failures, and dynamically adapt to changing workloads without service interruptions. The integration of artificial intelligence further extends these capabilities by introducing predictive monitoring, anomaly detection, intelligent resource scheduling, automated fault recovery, and adaptive workload management. Together, these technologies significantly reduce infrastructure complexity while improving overall system performance and business continuity.

Predictive decision intelligence emerges as one of the most influential components of autonomous enterprise computing. Rather than relying solely on historical reporting and human intuition, organizations increasingly utilize machine learning algorithms capable of forecasting operational events, identifying future business opportunities, estimating financial risks, optimizing supply chains, predicting customer behavior, and supporting strategic planning. Predictive intelligence transforms enterprise management from reactive problem-solving toward proactive decision-making, allowing organizations to anticipate challenges before they occur and implement preventive measures accordingly. Such capabilities improve organizational responsiveness while minimizing uncertainty across both operational and strategic decision processes.

Another major contribution of autonomous enterprise computing lies in operational automation. Artificial intelligence eliminates repetitive manual tasks through intelligent workflow automation, robotic process automation, predictive maintenance, automated security management, and self-healing infrastructure. These automation capabilities reduce human intervention in routine administrative processes while improving consistency, reliability, and execution speed. Employees consequently devote greater attention to innovation, customer engagement, and strategic planning instead of repetitive operational activities. This shift enhances workforce productivity while supporting organizational transformation toward knowledge-driven business models.

The findings also demonstrate significant improvements in enterprise cybersecurity through AI-enabled threat intelligence. Intelligent behavioral analytics, anomaly detection, automated incident response, and continuous monitoring collectively strengthen organizational security against increasingly sophisticated cyber threats. Rather than depending solely upon predefined security signatures, AI systems identify unknown attack patterns through behavioral deviations and predictive modeling. Automated containment procedures further minimize attack propagation while accelerating incident response. These capabilities become increasingly essential as enterprise environments continue expanding across hybrid cloud infrastructures, distributed applications, Internet of Things devices, and remote workforce ecosystems.

Resource optimization constitutes another critical outcome of autonomous enterprise computing. Predictive analytics accurately estimates future infrastructure requirements, enabling cloud platforms to allocate computing resources dynamically according to anticipated workloads. This adaptive allocation minimizes unnecessary infrastructure expenditures while maintaining application performance under varying demand conditions. Organizations consequently achieve better financial efficiency through reduced operational costs, lower energy consumption, improved infrastructure utilization, and optimized cloud service expenditures. Such economic benefits reinforce the business value of intelligent enterprise computing beyond purely technical performance improvements.

The study further emphasizes that autonomous enterprise computing extends beyond technological innovation by fundamentally transforming organizational management practices. Intelligent decision support systems improve collaboration across departments by providing unified access to real-time operational intelligence. Enterprise leaders receive comprehensive analytical insights supported by predictive models, enabling evidence-based decision-making across finance, operations, marketing, supply chain management, cybersecurity, and customer relationship management. This integrated intelligence enhances organizational coordination while supporting more effective long-term strategic planning.

Nevertheless, successful implementation requires careful attention to organizational readiness, workforce development, governance, regulatory compliance, and ethical artificial intelligence practices. The migration of legacy applications into cloud-native environments remains technically demanding and often requires substantial modernization efforts. Machine learning systems must be continuously monitored, validated, and retrained to maintain predictive accuracy within evolving business environments. Additionally, organizations must address challenges associated with algorithmic transparency, fairness, data privacy, cybersecurity governance, and regulatory compliance. Establishing robust governance frameworks will therefore remain essential for ensuring trustworthy and responsible autonomous enterprise operations.

The broader implications of autonomous enterprise computing extend across virtually every industry sector, including healthcare, finance, manufacturing, education, telecommunications, transportation, retail, government administration, and smart cities. As enterprises continue generating increasingly large volumes of operational data, intelligent cloud-

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native architectures provide the computational foundation necessary for extracting actionable knowledge from complex information ecosystems. The convergence of artificial intelligence, distributed computing, predictive analytics, edge computing, and cloud automation creates unprecedented opportunities for developing highly adaptive digital enterprises capable of autonomous learning and continuous optimization.

In summary, Autonomous Enterprise Computing through AI-driven cloud-native architecture and predictive decision intelligence represents a major advancement in enterprise digital transformation. The integrated framework significantly improves operational efficiency, resource utilization, predictive capability, cybersecurity, resilience, scalability, customer satisfaction, and strategic decision-making. The research demonstrates that organizations adopting intelligent autonomous computing architectures are better positioned to respond effectively to changing market conditions, technological disruptions, and evolving customer expectations. As artificial intelligence technologies continue advancing, autonomous enterprise computing will increasingly become a fundamental component of next-generation digital enterprises, enabling sustainable innovation, operational excellence, and long-term organizational competitiveness.

VI. FUTURE WORK

Future research on Autonomous Enterprise Computing should concentrate on expanding the intelligence, adaptability, security, and sustainability of AI-driven cloud-native ecosystems. One promising direction involves developing self-evolving artificial intelligence models capable of continuously learning from changing enterprise environments without extensive manual retraining. Existing machine learning systems often require periodic updates to maintain predictive accuracy due to evolving business processes and concept drift. Future autonomous enterprises should incorporate lifelong learning algorithms, reinforcement learning, transfer learning, and federated learning techniques that enable continuous adaptation while preserving privacy and minimizing computational overhead. Such capabilities would allow enterprise systems to become increasingly autonomous over time while maintaining reliable performance across dynamic operational environments.

Another important research direction involves integrating edge computing with autonomous enterprise platforms. As Internet of Things devices, industrial sensors, autonomous vehicles, smart manufacturing systems, and wearable technologies continue generating massive real-time data streams, processing information closer to data sources becomes increasingly necessary. Future enterprise architectures should intelligently coordinate computational workloads across cloud data centers, edge devices, and distributed infrastructure according to latency requirements, bandwidth availability, energy consumption, and application priorities. AI-driven workload orchestration across hybrid cloud-edge environments represents a significant opportunity for improving responsiveness while reducing communication delays and infrastructure costs.

Future investigations should also emphasize explainable artificial intelligence and trustworthy autonomous decision-making. Many existing predictive models operate as complex black-box systems whose decision processes remain difficult for enterprise stakeholders to interpret. Research should therefore develop transparent AI frameworks capable of providing understandable explanations for predictions, recommendations, and autonomous actions. Improved explainability would strengthen user confidence, facilitate regulatory compliance, support auditing processes, and enable organizations to identify potential algorithmic biases before they affect business operations. Combining explainable AI with ethical governance frameworks will become increasingly important as autonomous enterprise systems assume greater responsibility for strategic decision-making.

Cybersecurity research should continue exploring autonomous defense mechanisms capable of responding intelligently to rapidly evolving cyber threats. Future enterprise security architectures may incorporate autonomous cyber agents that collaboratively identify attack patterns, share threat intelligence, predict emerging vulnerabilities, and coordinate defensive responses across distributed infrastructures. Integrating quantum-resistant cryptographic techniques, blockchain-based identity management, zero-trust security models, and AI-powered behavioral authentication could further strengthen enterprise resilience against future cybersecurity challenges. Such intelligent security ecosystems would provide continuous protection while minimizing manual intervention by cybersecurity professionals.

Finally, future work should investigate sustainable and energy-efficient autonomous enterprise computing. As artificial intelligence workloads and cloud infrastructures continue expanding globally, reducing environmental impact becomes increasingly important. Research should develop intelligent resource optimization algorithms capable of minimizing energy consumption, carbon emissions, cooling requirements, and hardware waste while maintaining high computational performance. Green cloud computing, renewable energy integration, carbon-aware workload scheduling, and intelligent infrastructure management represent promising research directions for supporting environmentally

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sustainable digital transformation. By integrating sustainability objectives with autonomous decision intelligence, future enterprise computing platforms can simultaneously achieve operational excellence, economic efficiency, and environmental responsibility, thereby supporting long-term organizational resilience and global sustainable development.

REFERENCES

1. Buyya, R., Broberg, J., & Goscinski, A. (Eds.). (2011). Cloud computing: Principles and paradigms. Wiley.
2. Mannem, S. (2023). Intelligent service behavior analysis for early cyber threat prediction. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8077–8088. https://doi.org/10.15662/IJRPETM.2023.0601008
3. Tasleem, N. (2017). Service catalog optimization in HR. International Journal of Applied Research, 3, 1090-1097.
4. Anand, L., & Neelanarayanan, V. (2019). Liver disease classification using deep learning algorithm. BEIESP, 8(12), 5105-5111.
5. Vimal Raja, G. (2022). Leveraging Machine Learning for Real-Time Short-Term Snowfall Forecasting Using MultiSource Atmospheric and Terrain Data Integration. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 5(8), 1336-1339.
6. Soni, H., & Ramamurthy, P. (2023). Designing modular AI architectures for enterprise scale: From monolithic models to composable AI systems. International Journal of Research Publications in Engineering, Technology and Management, 6(1), 8136–8141.
7. Govindan, V. (2023). AI-powered optimization of non-production environments: Turning constraints into business value. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8089–8104. https://doi.org/10.15662/IJRPETM.2023.0601009
8. Kotla, Mutha Ravi Tej (2022). Intelligent cloud-native banking: Leveraging machine learning for secure and scalable digital financial services. International Journal of Engineering and Technology Research, 7(1), 58–81. https://doi.org/10.34218/IJETR_07_01_005
9. Syed, S. (2023). A GxP-compliant integrated ERP framework for synchronizing OPM, SCM, and quality lab systems in pharmaceutical manufacturing. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8064–8076. https://doi.org/10.15662/IJRPETM.2023.0601007
10. Balaji, K. V., & Sugumar, R. (2022, December). A Comprehensive Review of Diabetes Mellitus Exposure and Prediction using Deep Learning Techniques. In 2022 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI) (Vol. 1, pp. 1-6). IEEE.
11. Veershetty, G. (2019). From Legacy Back Office to Intelligent Utility Enterprise a Practitioner Case Study of SAP Cloud Transformation and Utility IT Landscape Modernization. American International Journal of Computer Science and Technology, 1(1), 23-27.
12. Garg, A. (2022). Using interpretable machine learning identify factors contributing to COVID-19 cases in the United States. In Novel AI and Data Science Advancements for Sustainability in the Era of COVID-19 (pp. 113-158). Academic Press.
13. Navandar, P. (2022). Adaptive SAP security control framework for ML driven anomaly detection, role based access hardening, and continuous compliance monitoring in SAP S/4HANA environments. International Journal of Engineering & Extended Technologies Research (IJEETR), 4(3), 4939–4952. https://doi.org/10.15662/IJEETR.2022.0403005
14. Gummadi, V. P. K. (2020). API design and implementation: RAML and OpenAPI specification. Journal of Electrical Systems, 16(4).
15. Mohammed, S. (2022). Designing secure zero trust architectures for global enterprise environments. International Journal of Science, Research and Technology (IJSRAT), 5(6), 8953–8956.
16. Raja, G. V. (2022). Integrating network forensics with data mining for advanced cybercrime investigation. International Journal of Engineering & Extended Technologies Research (IJEETR), 4(5), 5321–5326.
17. Gandikota, S. P. (2023). An elastic cloud-native framework for processing millions of IoT events per second in smart grid environments. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8049–8063. https://doi.org/10.15662/IJRPETM.2023.0601006
18. Soundappan, S. J. (2022). AI-Based Fault Detection and Isolation for Reliability in Modern Power Systems. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 5(4), 7106-7110.
19. Chettiyar, S. S. S. (2023). A vendor-neutral omnichannel conversational payment architecture for conversational commerce integrating BYOP, native solutions, and PCI compliance. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8124–8135. https://doi.org/10.15662/IJRPETM.2023.0601012

20. Dhinakaran, D., Prathap, P. J., Selvaraj, D., Kumar, D. A., & Murugeshwari, B. (2022). Mining privacy-preserving association rules based on parallel processing in cloud computing. International Journal of Engineering Trends and Technology, 70(3), 284-294.
21. Sarngadharan, S. (2023). Federated data pipelines enabling continuous contract and asset state traceability. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8114–8123. https://doi.org/10.15662/IJRPETM.2023.0601011
22. Chenna, S. (2023). Solution-led integration architecture in Oracle EBS: A dual case study from foundational enterprise engagements. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(1), 8105–8113. https://doi.org/10.15662/IJRPETM.2023.0601010
23. Raj, A. A., & Sugumar, R. (2022, December). Monitoring of the Social Distance between Passengers in Real-time through Video Analytics and Deep Learning in Railway Stations for Developing the Highest Efficiency. In 2022 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI) (Vol. 1, pp. 1-7). IEEE.
24. Konakalla, K. (2020). Automated commission calculation and sales quota management in Salesforce: A code-driven approach for sales efficiency. International Journal, 7, 125-127.
25. Polamreddy, V. R. (2022). Architecting Hybrid Synchronization Models to Enable Safe International Platform Transitions. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 5(1), 6216-6229.
26. Manda, P. (2022). Implementing hybrid cloud architectures with Oracle and AWS: Lessons from mission-critical database migrations. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 5(4), 7111–7122.
27. Vayyasi, N. K. (2019). Reimagining financial compliance automation: Using Java microservices and generative AI on AWS Bedrock for regulatory intelligence. International Journal of Future Innovative Science and Technology (IJFIST), 2(3), 1992–1210.
28. Tamilvizhi, T., Surendran, R., Anbazhagan, K., & Rajkumar, K. (2022). Research Article Quantum Behaved Particle Swarm Optimization-Based Deep Transfer Learning Model for Sugarcane Leaf Disease Detection and Classification.
29. Shewale, V. (2022). Third-Party and Supply Chain Risk in Oil & Gas. International Journal of Future Innovative Science and Technology (IJFIST), 5(6), 9596.
30. Parasa, M. (2022). Addressing the underutilization of exit interview data: A structured AI-assisted framework for actionable workforce insights in SAP SuccessFactors. Global Scientific and Academic Research Journal of Multidisciplinary Studies, 1(6), 42–52. https://gsarpublishers.com/abstract-2326
31. Vanitha, C., Sanmugam, A., Yogananth, A., Rajasekar, M., Kuppusamy, P. G., & Devasagayam, G. (2022). A facile synthesis of polyaniline-WO3 hybrid nanocomposite for enhanced dopamine detection. Materials Letters, 328, 133149.
32. Jagadeesh, S., & Sugumar, R. (2017). A Comparative study on Artificial Bee Colony with modified ABC algorithm. European Journal of Applied Sciences, 9(5), 243-248.
33. Juvvadi, R. R. (2019). Smart contracts in supply chain finance: Automating accounts payable and the three-way match. Journal of Information Systems Engineering and Management, 4(1), 1–12.
34. Chaganti, S. (2022, November). An AI-driven spatiotemporal crowd orchestration platform for large-scale theme parks: Hybrid machine learning, behavioural modelling, and real-time decisioning for safe and efficient guest flow. International Journal on Recent and Innovation Trends in Computing and Communication, 10(11), 275–283.
35. Anand, L., & Syed Ibrahim, S. P. (2018). HANN: a hybrid model for liver syndrome classification by feature assortment optimization. Journal of medical systems, 42(11), 211.
36. Vankayala, S. C. (2020). Reinventing test automation reliability: Adaptive locator intelligence and self-healing execution pipelines for enterprise QA. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 6(1), 226–242. https://doi.org/10.32628/CSEIT23906127.
37. Vimal, V. R., Anandan, P., & Kumaratharan, N. (2022). Heart Disease Diagnosis Using Electrocardiography (ECG) Signals. Intelligent Automation & Soft Computing, 32(1).
38. Mathew, A. (2022). Leveraging Big Data Analytics to Power AI and ML (Machine Learning) Automation. Educational Research (IJMCER), 4(5), 131-134.
39. Yamsani, N. (2018). Operationalizing regulatory governance through enterprise master data design: A practical examination of OFAC, KYC, and GDPR controls at Elavon. International Journal of Scientific Research & Engineering Trends, 4(6). https://doi.org/10.5281/zenodo.18196005
40. Feng, X., Guo, C., Jiao, T., & Song, J. (2022). A maturity model for AI-empowered cloud-native databases: From the perspective of resource management. Journal of Cloud Computing, 11, Article 39. https://doi.org/10.1186/s13677-022-00318-1