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JOURNAL OF
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RESEARCH ARTICLE

Revolutionizing stock management with IoT: Real-time visibility, automation, and efficiency

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Abstract: The rapid advancement of Internet of Things (IoT) technologies has revolutionized stock and inventory management by facilitating real-time visibility, automation, and data-informed decision-making all of which replace error-prone and repeated ... manual systems with connected sensors, Radio Frequency Identification (RFID) tags, and smart Devices that, in real-time, track goods through warehouses and supply chains. As a result of this transformation, inefficiencies are exacerbated, loss decreases, and responsiveness to unpredictable market demand is increased. Looking into the future, the inventory management work of disruptive technology is aided by innovations such as Artificial Intelligence (AI), blockchain, edge computing, and digital twins. AI can boost forecasting and predictive analytics to levee supply with demand more effectively while blockchain can provide transparency and security from tampering due to their immutable, transaction ledgers. Additionally, edge computing capabilities enable low-latency data processing at the source of collection. Digital twins reconstruct physical inventory systems into virtual models to simulate, explore, and develop risk management functions. When combining these innovative technologies, a smarter, safer, and evolved inventory ecosystem will be formed; an environment that provides organizations with a competitive advantage by permitting more effective use of efficiency, transparency, and escalation in resilience attributes in a globally complex marketplace.

Keywords: IoT, Inventory management, AI, Machine learning, Blockchain, Supply chain, Edge computing, Digital twins, Stock tracking, Smart warehouses

Introduction

In the contemporary company landscape, proficient stock or inventory management has emerged as a crucial factor in operational success and consumer happiness [1-3]. The capacity to sustain ideal inventory levels, monitor material movement, and swiftly adapt to demand variations significantly influences an organization's efficiency and profitability across manufacturing, retail, and logistics sectors. As global supply chains get more intricate, firms face persistent pressure to reduce inventory expenses while maintaining product availability [4-5].

Notwithstanding the strategic significance of inventory management, conventional methods persistently encounter numerous obstacles. Manual procedures, intermittent inventory assessments, spreadsheet-dependent monitoring, and isolated data systems can lead to inefficiencies, inaccuracies, and delays [6]. Stock inconsistencies, misplacement, overstocking, and recurrent stockouts are prevalent challenges that diminish operational transparency and escalate expenses. Moreover, these systems provide restricted real-time visibility, hindering decision-makers' ability to proactively address inventory-related issues.

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Received: 31/05/25, Accepted: 27/09/25, Published Online: 07/10/25

As industries endeavor to modernize and enhance agility, the constraints of traditional inventory systems have facilitated digital change. In this environment, the Internet of Things (IoT) has emerged as a transformative technology that is redefining inventory management throughout the supply chain [7]. The Internet of Things (IoT) facilitates seamless data acquisition, real-time surveillance, and automated decision-making through the integration of intelligent devices, sensors, Radio Frequency Identification (RFID) tags, and communication modules into physical inventory and infrastructure [8].

IoT-enabled inventory management enables enterprises to monitor stock intricately, assess inventory conditions, anticipate replenishment requirements, and enhance warehouse efficiency [9]. The acquisition of real-time data guarantees enhanced precision, expedited response times, and diminished human involvement. Sensors can identify low inventory levels and initiate automatic restocking, whilst Radio Frequency Identification (RFID) systems can monitor item movement across many locations with minimal operator intervention [10]. These features diminish shrinkage, augment forecasting precision, and promote total inventory visibility.

Moreover, IoT solutions can be connected with cloud platforms and enterprise resource planning (ERP) systems to establish a cohesive, intelligent inventory environment. This connectivity not only provides data-driven insights but also offers predictive analytics, allowing organizations to forecast demand and adjust accordingly [11]. In sectors managing perishable or sensitive goods, IoT can oversee environmental variables like temperature and humidity to guarantee product quality and regulatory adherence.

As firms progressively embrace Industry 4.0 ideas, the significance of IoT in inventory management is anticipated to grow further. The Internet of Things (IoT) is revolutionizing stock management by changing it from a reactive chore into a purposeful, proactive process, facilitating smart warehouses and autonomous inventory systems [12]. This article analyses the transformative impact of IoT on inventory management, investigates its components and uses, and addresses the advantages, problems, and future prospects of this nascent technology within the framework of supply chain optimization.

Comprehending IoT within the Framework of Inventory Management

The Internet of Things (IoT) has emerged as a transformative tool for inventory and stock management in contemporary supply chains. It facilitates instantaneous connection between tangible items and digital systems, thereby automating oversight, enhancing precision, and diminishing operational expenses. This section examines the principles of IoT and its role in enhancing stock management efficiency [13].

Definition of IoT Essential Elements (Sensors, Connectivity, Data Processing)

The Internet of Things (IoT) is a network of interconnected physical devices that gather and transmit data through the internet or other communication networks. In inventory management, IoT facilitates uninterrupted data exchange among storage systems, tracking instruments, and decision-making platforms [14].

The Internet of Things (IoT) comprises three primary components: sensors, networking modules, and data processing units. Sensors are integrated into devices to collect data such as product quantity, weight, temperature, or movement. Connectivity modules (Wi-Fi, Bluetooth, Zigbee, LoRa, or cellular networks) relay sensor data to cloud or edge computing platforms [15]. Figure 1 illustrates how various IoT components Radio Frequency Identification (RFID) tags, barcode scanners, and cloud dashboards interact in a smart warehouse. These devices enhance visibility and streamline inventory control through real-time data exchange.

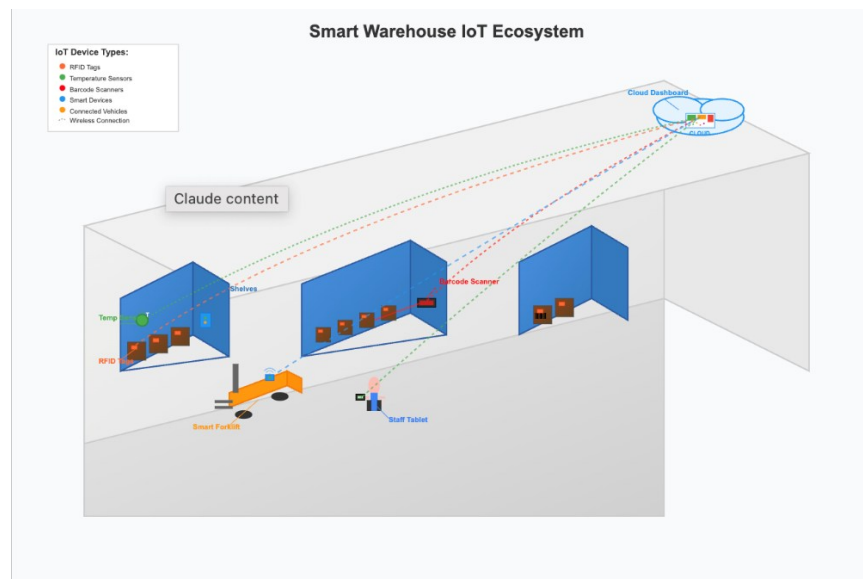


Figure 1: A modern warehouse equipped with IoT devices for real-time monitoring, inventory tracking, and cloud integration

Upon transmission, data processing units evaluate this information to extract insights, identify trends, or initiate automated actions such as reorder requests. These components function collaboratively to deliver real-time insights about inventory status, allowing companies to enhance storage efficiency, minimize errors, and make proactive decisions. The fundamental framework of smart inventory systems, IoT guarantees that stock data is precise, current, and easily available across the supply chain [16].

The Role of IoT in Inventory Management

The Internet of Things improves inventory management through continuous monitoring, real-time information, and data-informed decision-making. Conventional techniques frequently entail manual inventory assessments and regular audits, both of which are labour-intensive and susceptible to inaccuracies [17]. The Internet of Things alleviates these issues through the automation of inventory processes.

A notable advantage is immediate inventory transparency. Utilizing intelligent sensors and monitoring systems, organizations may oversee inventory levels, item placements, and movement across several sites. This mitigates overstocking, understocking, and product loss. For instance, should inventory levels fall beyond a specified threshold, an IoT device might autonomously alert managers or initiate restocking orders [18].

Automation and predictive analytics represent further significant benefits. Historical inventory data gathered via IoT can be evaluated to predict demand trends, assisting firms in preparing for high seasons or mitigating excess stock during low-demand intervals. Thus, IoT facilitates efficient inventory management and reduces storage expenses [19].

Furthermore, risk reduction becomes more effective. IoT devices can monitor environmental variables such as temperature and humidity, guaranteeing that delicate items are maintained under ideal circumstances [20]. Alerts may be generated in the event of deviation, thereby minimizing spoiling or damage. In summary, IoT enhances daily inventory operations and facilitates strategic inventory planning, rendering it a crucial instrument in contemporary supply chains.

Categories of IoT Devices Utilized (Radio Frequency Identification (RFID), Barcode Scanners, Global Positioning System (GPS), etc.)

Various IoT-enabled devices are utilized to enhance intelligent inventory systems, each playing a distinct role in the effective tracking, monitoring, and management of stock [21]. Radio Frequency Identification (RFID) is extensively utilized for tracking items at the individual level.

Passive Radio Frequency Identification (RFID) tags are affixed to products and wirelessly scanned by Radio Frequency Identification (RFID) readers, facilitating bulk scanning without the necessity of line-of-sight. Active Radio Frequency Identification (RFID), equipped with an internal power source, facilitates long-range monitoring and is advantageous for tracking substantial cargo or assets [22-23].

Barcode and QR code scanners, despite being conventional, continue to be vital instruments in inventory management. When linked to cloud-based systems, they promptly update inventory data upon scanning, minimizing human entry and errors [24]. QR codes provide enhanced information store capacity and may be scanned with smartphones. Global Positioning System (GPS) trackers are utilized in logistics and transportation to oversee shipments in real time. They assist in mitigating loss, enhancing delivery schedules, and facilitating route optimization. Global Positioning System (GPS) data can be utilized to activate geofencing notifications when a shipment strays from its designated route [25].

Additional devices comprise intelligent shelves and bins fitted with weight sensors or Radio Frequency Identification (RFID) readers for stock level detection, environmental sensors for temperature and humidity regulation, and IoT gateways that aggregate data from devices and transmit it to cloud platforms for processing [26]. Each of these technologies contributes a layer of intelligence, guaranteeing a responsive, automated, and precise inventory management system.

Utilization of IoT in Inventory Management

The incorporation of IoT in inventory management has profoundly altered the methods of monitoring, replenishing, and controlling stock. IoT solutions facilitate informed decision-making, minimize manual involvement, and guarantee supply chain transparency through real-time tracking and predictive analytics. This section examines principal applications of IoT in stock and inventory management [27].

Real-time Inventory Monitoring

A significant application of IoT in inventory management is real-time inventory tracking. Businesses may continuously monitor the location, quantity, and quality of commodities along the supply chain using Radio Frequency Identification (RFID) tags, barcode scanners, Global Positioning System (GPS) systems, and sensors [27]. This transparency enables stakeholders to ascertain the precise location and status of a product, whether it is in storage, in transit, or displayed on a shelf.

Real-time tracking reduces mismatches between physical stock and inventory records, enhancing stock accuracy and diminishing shrinkage caused by theft, damage, or misplacement. This also diminishes the necessity for manual inventory assessments and regular audits [28]. Moreover, warehouse managers can expedite decisions pertaining to restocking, order fulfilment, and space management. In multi-location operations, real-time tracking guarantees centralized oversight and coordination among locations. This solution optimizes operational efficiency, improves customer service through availability, and decreases inventory mistake costs [29].

As shown in Figure 2, IoT-based inventory systems present dynamic dashboards where managers can monitor inventory changes, set thresholds, and respond to supply chain events instantly minimizing stock-outs and delays

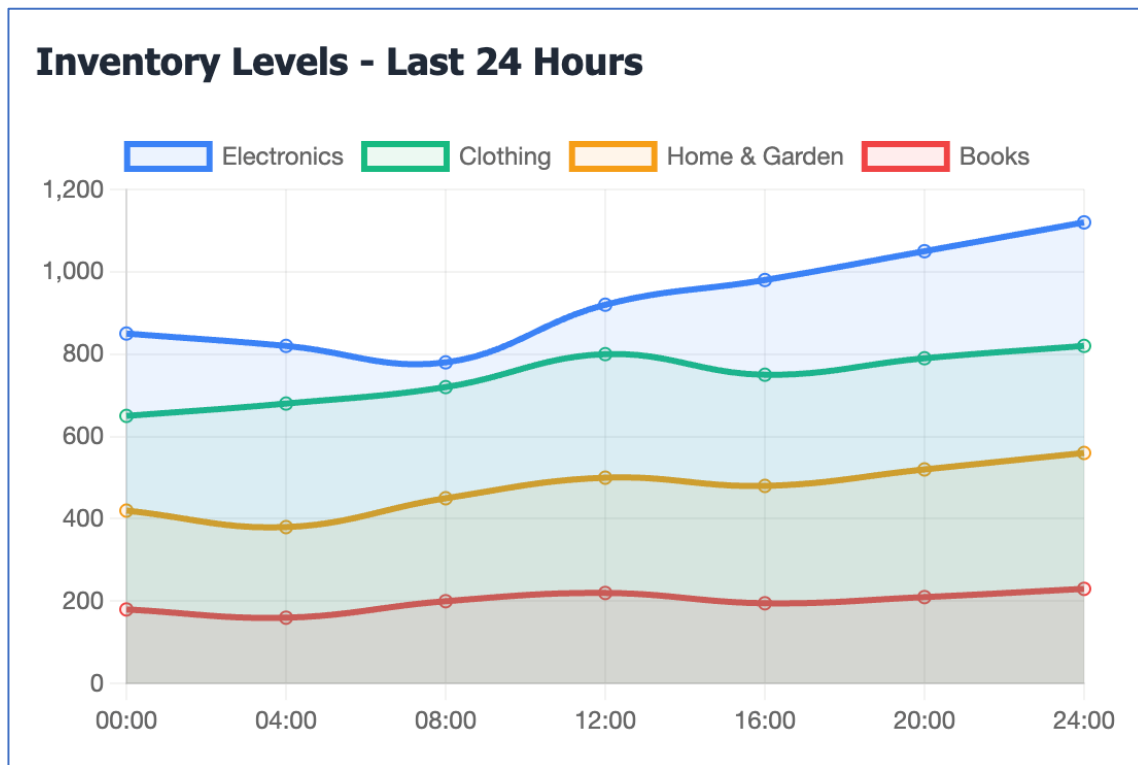


Figure 2: Real-time inventory tracking dashboard powered by IoT, providing actionable insights and instant stock visibility

Automated Inventory Replenishment

Automated stock replenishment is an essential capability facilitated by IoT systems, particularly in sectors with consistent demand where delays may lead to production interruptions or revenue loss. IoT sensors and interconnected systems continuously monitor inventory levels. The system may autonomously initiate replenishment orders when products drop below established thresholds, eliminating the necessity for human involvement [30].

This procedure is especially beneficial in high-volume retail or manufacturing settings, where even brief stockouts might impede operations. A garment production line may cease operations if attachments such as buttons or zippers are lacking [31]. IoT-enabled systems mitigate such disruptions by facilitating prompt resupply.

Furthermore, automated systems can be coupled with supplier platforms to optimize procurement processes. This not only conserves time but also facilitates dynamic ordering based on real-time usage trends instead of fixed reorder thresholds [32]. Consequently, enterprises can diminish holding costs, avert overstocking, and sustain ideal inventory levels that correspond with actual demand.

Predictive Analytics for Demand Projection

IoT devices produce substantial quantities of real-time data concerning inventory fluctuations, consumer transactions, seasonal patterns, and usage behaviours. By employing predictive analytics on this data, firms can precisely anticipate future demand and modify their inventory planning accordingly [33].

IoT sensors in a retail environment can monitor product popularity, movement velocity, and customer dwell time in designated aisles. These insights facilitate the identification of fast-moving and slow-moving items, enabling firms to optimize shelf space and product assortment [34]. In manufacturing, predictive analytics can forecast raw material requirements by analysing current production rates and past consumption data.

By effectively forecasting demand, organizations can reduce the risk of overproduction or stock shortages. This is especially crucial for enterprises experiencing seasonal fluctuations or marketing initiatives. Predictive analytics facilitates enhanced supplier negotiating, optimum warehouse space utilization, and increased customer satisfaction via timely product availability. In summary, it transforms unrefined IoT data into meaningful business knowledge [35].

Monitoring of Cold Chain for Perishable Goods

In sectors such as food, pharmaceuticals, and chemicals, preserving particular environmental conditions is crucial for product integrity. The Internet of Things (IoT) is essential in cold chain management, facilitating the ongoing monitoring of temperature, humidity, light exposure, and other crucial characteristics [36].

Intelligent sensors installed in storage units, transport vehicles, or packing materials can monitor environmental conditions in real time. Should any metric surpass the established thresholds, the system promptly notifies relevant staff, facilitating swift remedial measures [37]. This minimizes spoilage, guarantees adherence to safety rules, and improves traceability.

In pharmaceutical supply chains, vaccinations or medications typically require storage at temperatures ranging from 2 to 8 degrees Celsius. Any divergence may render them ineffective. IoT-based cold chain solutions not only record temperature but also incorporate Global Positioning System (GPS) for position tracking and cloud platforms for remote monitoring [38].

These systems offer comprehensive visibility, facilitating regulatory compliance (e.g., FDA, WHO) and minimizing waste resulting from undetected breaches. Ultimately, the Internet of Things guarantees that perishable and delicate commodities are delivered to consumers in ideal condition.

Intelligent Shelving and Warehouse Automation

Intelligent shelving and automated inventory systems exemplify a significant application of IoT in inventory management. Smart shelves utilize weight sensors, Radio Frequency Identification (RFID) readers, or vision systems to identify when an item is added or removed [39]. This facilitates real-time updates of inventory levels and can immediately initiate replenishment notifications. In retail settings, intelligent shelves ensure adherence to planograms, promptly identify out-of-stock conditions, and enhance overall shop efficiency. They additionally provide dynamic pricing contingent upon inventory levels or expiration dates, hence mitigating waste and enhancing sales margins [40].

Warehouse automation, facilitated by IoT, encompasses autonomous mobile robots (AMRs), automated guided vehicles (AGVs), and robotic picking systems. These technologies depend on sensor networks, Global Positioning System (GPS), and artificial intelligence to locate storage areas, retrieve objects, and execute orders with minimal human intervention [41].

This degree of automation not only augments speed and precision but also improves worker safety and diminishes labour expenses. Integration with warehouse management systems (WMS) facilitates smooth coordination among stocking, picking, packing, and shipping processes. Consequently, enterprises gain from expedited order processing, enhanced throughput, and optimum spatial usage.

Internet of Things Architecture for Inventory Management

The effective use of IoT in inventory management depends significantly on a meticulously designed architecture that integrates hardware, software, and communication protocols to establish an efficient, intelligent, and automated stock system. This architecture facilitates seamless connection between physical devices, data platforms, and enterprise applications [42]. The subsequent subsections delineate the essential elements of IoT design concerning stock management.

Hardware Configuration: Sensors, Gateways, Actuators

The cornerstone of every IoT-driven inventory management system is its hardware configuration. This comprises an ecosystem of sensors, actuators, and gateways that collaboratively capture and send data [43].

Sensors are employed to monitor diverse physical factors including temperature, humidity, weight, motion, and inventory levels. Typical instances comprise Radio Frequency Identification (RFID) tags for item identification, infrared sensors for item detection, load cells for monitoring shelf weight, and temperature sensors for perishable products. These sensors gather real-time data from storage sites, shelves, or transport units [44]. Figure 3 presents a standard IoT architecture used in inventory control, highlighting the interaction between physical warehouse elements and enterprise software. Each layer from sensors to cloud dashboards plays a critical role in system functionality.

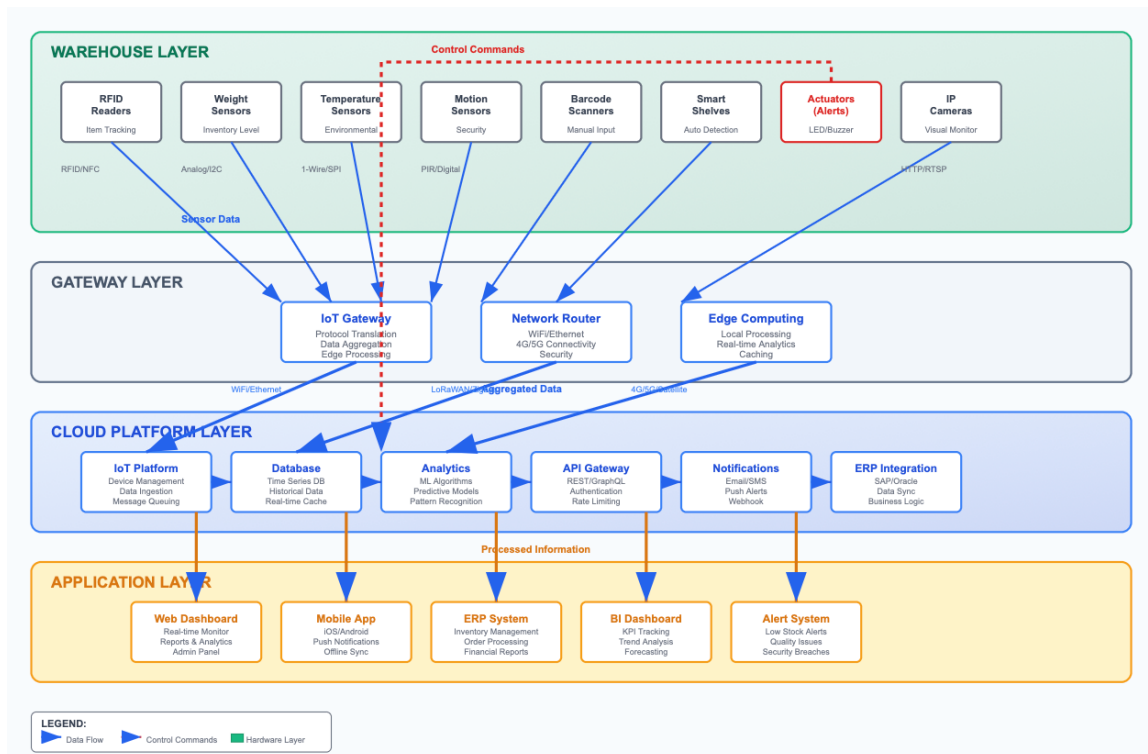


Figure 3: IoT architecture for stock management, integrating hardware, cloud computing, Enterprise Resource Planning (ERP) systems, and analytics dashboards

Actuators are devices that respond to the data received. In inventory management, actuators can activate warnings, commence conveyor belts, or regulate environmental conditions in refrigerated storage [45]. For instance, when a temperature sensor identifies an increase beyond the permissible range, an actuator may initiate a cooling system or sound an alarm. Gateways function as intermediaries between sensors/actuators and cloud-based systems [46]. They consolidate sensor data and perform pre-processing before to transmission over the internet or a private network. Gateways facilitate interoperability across diverse devices and are crucial for protocol translation, data filtration, and localized decision-making in edge computing contexts. This hardware layer constitutes the foundation of the IoT infrastructure, enabling data acquisition and physical system management.

Software integration: Cloud platforms, Enterprise Resource Planning (ERP) systems, dashboards

The efficacy of IoT in inventory management is significantly improved by strong software integration. After the data is gathered by physical components, it must be processed, analysed, and visualized using various software platforms [47]. Cloud platforms offer scalable storage and computational capabilities, enabling the real-time storing and processing of substantial amounts of sensor data. Platforms such as AWS IoT, Microsoft Azure IoT Hub, and Google Cloud IoT provide analytical tools, data visualization capabilities, and integration APIs. These solutions facilitate remote access, provide real-time notifications, and employ predictive modelling [48].

Enterprise Resource Planning (ERP) systems are essential for integrating IoT-derived data with comprehensive company functions, including procurement, finance, and sales. Integrating IoT technologies with Enterprise Resource Planning (ERP) software such as SAP, Oracle, or Microsoft Dynamics provides the firm with a consolidated perspective on inventory levels, supply chain conditions, and demand projections [49]. This facilitates the automation of procurement choices, reduces human error, and enhances inventory turnover efficiency.

Dashboards offer intuitive interfaces that enable managers to oversee inventory KPIs, receive alerts, produce reports, and watch product movement in real time. These dashboards are frequently customisable and optimized for mobile use, facilitating stakeholders' access to actionable insights from any location [50]. Data-driven decision-making is expedited and enhanced in accuracy through intuitive software interfaces that illustrate patterns and anomalies.

Data Communication Protocols (MQTT, HTTP, etc.)

Data communication is an essential element of IoT architecture. The method of data transmission among devices, gateways, and cloud platforms dictates the speed, reliability, and security of the overall system. Various communication protocols are frequently employed in IoT-based inventory management systems [51]. MQTT (Message Queuing Telemetry Transport) is a lightweight publish-subscribe protocol suited for low-bandwidth, high-latency conditions. It is especially appropriate for inventory systems utilizing distributed sensors or mobile devices. MQTT facilitates asynchronous data transmission among devices while optimizing network utilization, rendering it favoured for real-time applications such as warehouse automation and cold chain monitoring [52].

HTTP (Hypertext Transfer Protocol) is a prevalent communication protocol, particularly for web applications and dashboards. Although more data-intensive than MQTT, HTTP exhibits strong compatibility with current IT infrastructure and facilitates RESTful APIs for seamless integration with Enterprise Resource Planning (ERP) systems, cloud databases, and online applications [53]. CoAP (limited Application Protocol) is a nascent protocol developed for limited networks and devices. Similar to HTTP, it employs a request/response mechanism but with considerably less overhead, rendering it appropriate for battery-powered devices in remote inventory sites [54].

Bluetooth Low Energy (BLE), Zigbee, and LoRaWAN exemplify short-range and long-range wireless protocols utilized for device-to-device communication in warehouses, retail environments, or transportation fleets. These protocols facilitate the formation of networks among IoT devices, permitting peer-to-peer communication without requiring direct internet connectivity [55]. Selecting the appropriate protocol is contingent upon the specific use case, network architecture, data volume, and latency specifications. A hybrid methodology—utilizing MQTT for telemetry data and HTTP for command/control operations—is frequently employed for optimal balance and adaptability [56].

The design of an IoT-based stock management system constitutes a meticulously organized network of hardware, software, and communication protocols. Sensors and actuators constitute the data-collection layer, gateways function as intermediaries, cloud platforms and enterprise resource planning (ERP) systems manage storage and analytics, while connection protocols facilitate uninterrupted data transmission [57]. Collectively, these components facilitate real-time insights, automation, and agility in inventory management processes. An effectively integrated architecture enhances efficiency and cost-effectiveness while positioning firms for future scalability and innovation.

Case Analyses / Sector Applications

The implementation of IoT in inventory management has allowed firms in several sectors to enhance stock optimization, minimize waste, and react to real-time demand with agility. This section analyses the integration of IoT technologies by prominent corporations in clothes and textiles, retail, e-commerce, and medicines to enhance their inventory management systems [58].

Clothing and Textile Industry

In the fashion and textile sector, overseeing various SKUs, numerous production phases, and worldwide distribution necessitates resilient inventory systems. The Internet of Things facilitates uninterrupted monitoring from raw materials to completed products, reducing delays and enhancing industrial efficiency [59].

Arvind, a leading textile producer, adopted radio frequency identification (RFID) technology throughout its facilities to track fabric rolls, trims, and garments in real time. Radio Frequency Identification (RFID) tags were affixed to each lot, facilitating comprehensive tracking throughout their Ahmedabad manufacturing facility [60]. Integrated dashboards automatically updated stock movement, decreasing inventory errors by more than 25% and facilitating timely restocking.

The global fashion retailer H&M use IoT-based logistics tracking across its supply chain to oversee inventory movement from textile suppliers to distribution facilities and retail locations [61]. Barcode scanners and data sensors facilitate real-time order tracking, thereby mitigating bottlenecks in warehouse operations. Moreover, smart shelves are implemented in select H&M stores across Europe, outfitted with pressure and proximity sensors to notify personnel when refilling is necessary. This system enhances inventory turnover and customer satisfaction.

Retail Supply Chains

Retailers are utilizing IoT to transition from reactive inventory management to predictive and automated solutions. The Internet of Things (IoT) guarantees that inventory levels correspond to genuine demand, minimizes stock shortages, and improves operational efficiency [62].

Zara, recognized for its nimble supply chain, utilizes Radio Frequency Identification (RFID) technology throughout its international network. The Radio Frequency Identification (RFID) tags affixed to garments provide real-time monitoring from distribution centers to retail displays. This facilitates the optimization of store layout, stock management, and immediate inventory visibility. Items tested in fitting rooms but not acquired are designated for restocking or reassessment, facilitating improved inventory management at the micro level [63].

Decathlon, a leading sporting goods company, has adopted IoT-enabled smart inventory systems that integrate Radio Frequency Identification (RFID) tagging with automated checkout stations. Each product possesses a tag that is automatically scanned at checkout, while updating inventory databases [64]. Their cloud-integrated solutions provide dynamic inventory replenishment and immediate identification of stockouts.

E-commerce and Logistics

E-commerce enterprises encounter difficulties in efficiently processing large, varied orders while ensuring promptness and precision. The Internet of Things enables effortless warehouse automation, instantaneous tracking, and predictive demand analysis. Amazon's warehouses are internationally acknowledged for their automation linked with IoT technology [67]. The company employs Kiva robots (now Amazon Robotics) for the sorting and transportation of items, in conjunction with barcode scanners and Radio Frequency Identification (RFID) readers to guarantee real-time inventory updates. All products in the warehouse are systematically mapped and monitored, significantly minimizing human inventory assessments [68].

GPS trackers integrated onto delivery vehicles allow clients to obtain real-time notifications regarding their shipments. Moreover, temperature sensors are employed in the Amazon Fresh grocery delivery sector to preserve the integrity of perishable items, notifying management of any deviations from the recommended storage range [69].

Flipkart incorporates IoT through automated sorting systems, GPS tracking for logistics, and intelligent dashboards for inventory viewing. These solutions enhance the efficiency of picking, packing, and last-mile

delivery, concurrently minimizing turnaround time. Their recent implementation of predictive analytics for stock allocation according to regional demand has enhanced fulfilment accuracy [70].

Pharmaceutical Inventory Management

The pharmaceutical sector requires precision, safety, and environmental regulation in inventory management. The Internet of Things facilitates real-time monitoring, ensures compliance, and mitigates stock losses resulting from spoilage or theft.

Pfizer employs IoT-based cold chain monitoring systems to guarantee that temperature-sensitive vaccines and biologics are maintained within designated temperature thresholds during transportation. Wireless temperature sensors interface with cloud platforms and alert operators in the event of any deviations, thereby assisting in maintaining drug efficacy and adherence to health laws [71].

Apollo Hospitals has implemented Radio Frequency Identification (RFID) and IoT sensors in their pharmacy stockrooms to monitor the movement of medications, surgical instruments, and high-value consumables [72]. Intelligent cabinets coupled with Enterprise Resource Planning (ERP) systems facilitate the maintenance of optimal inventory levels while mitigating theft and the utilization of expired stock. Their intelligent dashboards allow pharmacists to visualize the current inventory situation across several hospital units.

McKesson, a global leader in healthcare distribution, employs IoT and AI to oversee inventory across numerous pharmacies. They uphold stringent quality standards through the utilization of temperature and humidity sensors in their warehouses and transport vehicles [73]. Radio Frequency Identification (RFID) tagging facilitates the tracking of each batch of medication, guaranteeing authenticity and mitigating the risk of counterfeiting.

These industry examples illustrate the evolution of IoT from a novel concept to a vital facilitator of stock efficiency across many sectors. Companies such as Zara, Amazon, Pfizer, and Arvind demonstrate that the incorporation of IoT not only streamlines inventory management but also improves decision-making, regulatory compliance, and customer happiness [74]. As technology advances and expenses diminish, the importance of IoT in inventory management will expand, establishing a new standard for operational excellence across all sectors.

Advantages and Return on Investment

The incorporation of IoT (Internet of Things) into inventory management systems has proven transformative for enterprises aiming to enhance efficiency, minimize inaccuracies, and facilitate data-informed decision-making [75]. The Internet of Things (IoT) enhances inventory management efficiency through real-time tracking, automated data collecting, and seamless interaction with business systems, resulting in a quantifiable return on investment (ROI). This section examines the primary advantages firms derive from implementing IoT in stock management.

Enhanced Precision and Diminished Human Error

A primary and substantial advantage of IoT in inventory management is the marked enhancement in accuracy. Conventional inventory techniques, frequently reliant on human counting or data entry, are susceptible to inaccuracies stemming from exhaustion, miscommunication, or negligence [78]. The Internet of Things mitigates numerous dangers by automating data acquisition via sensors, Radio Frequency Identification (RFID) tags, and barcode scanners.

For instance, when Radio Frequency Identification (RFID) tags are integrated into product packaging, scanners may autonomously recognize and tally things as they progress through warehouses or retail settings [78]. This reduces inconsistencies between actual inventory and system documentation. Furthermore, automated methods diminish reliance on regular manual audits, which are labour-intensive and susceptible to errors.

Companies such as Zara and Amazon have reported enhanced inventory accuracy exceeding 95% with the implementation of Radio Frequency Identification (RFID) and barcode technology. This degree of accuracy diminishes order fulfilment inaccuracies, customer discontent, and superfluous reordering stemming from presumed shortages [78].

Mitigated Stock-outs and Excess Inventory

Stock-outs and overstocking constitute two of the most significant challenges in inventory management. A stock-out may result in lost sales and reduced client confidence, whereas overstocking immobilizes capital, escalates storage expenses, and heightens the danger of product obsolescence, especially in sectors such as fashion and electronics [79].

IoT-enabled systems can monitor inventory levels in real time and initiate alerts or actions when goods near minimal thresholds or surpass maximum restrictions. For instance, intelligent shelves equipped with weight or proximity sensors can alert warehouse managers regarding inventory levels without the necessity of manual inspections. This facilitates prompt restocking and prevents lost sales opportunities in retail [80].

Integrating IoT data with predictive analytics and demand forecasting models enables firms to achieve a more balanced and demand-responsive inventory plan. Decathlon employs Radio Frequency Identification (RFID) and cloud-based analytics to dynamically modify inventory according to regional purchasing trends, hence reducing stock-outs and surplus inventory [81].

Improved Operational Efficiency

Operational efficiency is fundamental to effective inventory management, and the Internet of Things (IoT) amplifies this across multiple operations. By centralizing automation, IoT diminishes the necessity for redundant processes like scanning, counting, and manual report creation [82].

In warehouses, IoT-enabled robots and automated guided vehicles (AGVs) maneuver and convey merchandise with limited human involvement. Amazon's Kiva robots exemplify efficiency; utilizing real-time inventory data, these robots minimize the time needed for item picking and packing, hence facilitating expedited order fulfilment [82].

Moreover, IoT devices can interface with Enterprise Resource Planning (ERP) platforms and online dashboards, providing centralized oversight of inventory across several locations [83]. This enhances interdepartmental communication, minimizes work redundancy, and expedites decision-making. Temperature and humidity sensors in storage facilities guarantee ideal storage conditions without the need for continuous personal oversight.

In the healthcare and food industries, cold chain monitoring guarantees that perishable commodities are stored and transported within permissible limitations. This results in reduced product losses and improves regulatory compliance, exemplified by Pfizer's vaccine distribution system that employs IoT sensors for comprehensive cold chain monitoring [84].

Financial Efficiency and Enhanced Decision-Making

Cost efficiency is a primary incentive for implementing IoT in inventory management. Although initial expenditures on IoT infrastructure (such as sensors, gateways, and software platforms) may be substantial, the long-term return on investment is persuasive. Cost savings arise from various factors: decreased labour expenses, diminished inventory inaccuracies, reduced waste, enhanced storage efficiency, and accelerated cycle times [85]. By diminishing reliance on manual processes, enterprises can reassign human resources to more valuable duties. Automated replenishment systems mitigate over-ordering and under-ordering, minimizing waste and ensuring procurement closely coincides with actual demand [86].

Furthermore, IoT-enabled data analytics facilitates strategic decision-making. Historical trends, usage patterns, and seasonal variations can be examined to enhance inventory levels, supplier contracts, and distribution strategies. Dashboards and notifications assist managers in making educated decisions

promptly, hence limiting hazards prior to their escalation [87]. Organizations such as McKesson and Apollo Hospitals have reported significant cost savings with the use of IoT in their inventory management systems. These encompass reduced storage and handling expenses, diminished stock loss due to expiration or theft, and enhanced procurement planning [88].

The integration of IoT in inventory management offers a significant value proposition. By enhancing precision and minimizing human error, organizations may exert stricter control over inventory records. The automation of monitoring and replenishment procedures guarantees reduced stock-outs and lowers surplus inventory [89]. Moreover, operational efficiency is improved with intelligent warehousing solutions, resulting in substantial cost reductions throughout the supply chain.

Ultimately, the return on investment from IoT-based inventory systems transcends simple financial benefits. Organizations gain from enhanced agility, elevated customer satisfaction, and a more robust framework for data-informed decision-making [90]. As IoT technologies advance, their integration into inventory and supply chain management is expected to become a strategic imperative rather than a mere choice.

Obstacles and Constraints

The use of IoT (Internet of Things) in inventory management presents various advantages, although its implementation is fraught with difficulties. Organizations, particularly in developing economies or conventional sectors, may encounter numerous challenges, including substantial initial investments and system compatibility concerns [91]. Comprehending these constraints is essential for creating resilient, scalable, and secure IoT-driven inventory systems. This section explores the primary problems related to IoT implementation in inventory management.

Cost of Implementation

A key obstacle to IoT adoption is the substantial initial expenditure necessary for hardware, software, and infrastructure implementation. Implementing IoT for inventory management necessitates the acquisition of smart sensors, radio frequency identification (RFID) tags, readers, IoT gateways, and networking equipment [92]. Additionally, cloud platforms or enterprise resource planning (ERP) software that can handle substantial quantities of real-time data must be incorporated into current systems.

Small and medium enterprises (SMEs) may find it financially onerous to acquire the necessary infrastructure and specialized expertise. Moreover, continuous expenses for device maintenance, software subscriptions, training, and system upgrades can build over time, rendering long-term budgeting imperative [93]. For instance, whilst corporations such as Amazon and Zara can allocate substantial resources to IoT-integrated warehouses and supply chains, smaller textile or garment manufacturers may find it challenging to attain comparable digital transformation without governmental assistance or strategic alliances.

Data Security and Privacy Issues

IoT systems produce and transmit substantial amounts of sensitive data, rendering data security and privacy a critical issue. Unauthorized access to inventory data, supplier information, or distribution patterns may result in severe repercussions, including theft, industrial espionage, or financial loss [94].

Security vulnerabilities frequently emerge from the multitude of linked devices, each serving as a potential access point for cyber-attacks. If insufficiently safeguarded, IoT devices may be vulnerable to exploitation via techniques such as spoofing, denial-of-service assaults, or malware infestations. The notorious Mirai botnet assault in 2016, which took advantage of inadequately secured IoT devices, highlighted the necessity of robust cybersecurity measures [95].

Data privacy becomes a significant concern, particularly in industries such as medicines and e-commerce, where inventory data may be associated with consumer or patient information [96]. Organizations are required to adhere to data protection legislation, including the General Data Protection Regulation (GDPR)

and India's Digital Personal Data Protection Act. Organizations must install end-to-end encryption, regular firmware updates, secure communication protocols (such as HTTPS or TLS), and multi-factor authentication solutions to address these challenges [97].

Integration with Legacy Systems

Numerous firms, especially those in operation for several decades, continue to depend on outdated inventory systems that were not engineered to integrate with contemporary IoT platforms. These legacy systems may be deficient in APIs, standardized data formats, or the computational capacity required for real-time processing [98]. The integration of IoT devices with these systems can be intricate and expensive. It frequently necessitates tailored middleware solutions, significant reprogramming, or even comprehensive renovations of current IT infrastructure. Furthermore, the staff may require reskilling or upskilling to proficiently run and manage the new integrated environment [99].

In the retail apparel sector, outdated POS (Point-of-Sale) systems may lack the capability for real-time synchronization with IoT-enabled inventory databases, resulting in data inconsistencies or delays. Addressing this technology disparity is crucial yet may be laborious and technically demanding [100].

Moreover, diverse IoT suppliers employ distinct communication standards, potentially leading to compatibility challenges when several device types are utilized throughout the supply chain. Open standards and interoperability frameworks continue to develop, presenting hurdles for smooth integration.

Scalability Challenges

IoT systems frequently demonstrate efficiency at a pilot scale but may face scaling challenges when deployed across numerous warehouses, regions, or product categories. Overseeing numerous devices, sensors, and data streams necessitates a resilient cloud architecture, effective network bandwidth, and a dependable data processing backend. As the scale expands, the intricacy of sustaining uptime, guaranteeing device calibration, and preventing communication delays also escalates. A singular point of failure, such as a network disruption or compromised firmware update, might impact the overall performance of the system [101].

Furthermore, enterprises must guarantee that their systems are capable of scaling both technically and economically. Incorporating new functions, such as AI-driven analytics or blockchain integration for traceability, frequently necessitates supplementary investment and specialized personnel [102]. Scalability is essential for sectors such as e-commerce, where firms like Flipkart and Myntra must handle variable inventory levels during peak demand periods, such as festive sales or flash promotions. In these situations, inadequate scalability may lead to delayed order fulfilment, inventory discrepancies, and diminished income.

Organizations must implement modular and cloud-native IoT architectures capable of horizontal scaling without significant disruptions. Collaborating with seasoned IoT solution providers and performing stress testing during the design process might mitigate these difficulties [103]. Although IoT has the capacity to transform stock management by improving efficiency, accuracy, and decision-making, it also presents a series of difficulties that require strategic resolution. Significant initial expenses, data security vulnerabilities, incompatibilities with existing systems, and scalability challenges might impede effective deployment, particularly for small and medium-sized enterprises and conventional sectors [104].

Nonetheless, through meticulous planning, incremental implementations, and compliance with optimal security and system integration protocols, these obstacles can be successfully alleviated. Recognizing and addressing these limits is essential for attaining sustainable ROI and establishing a future-ready inventory environment.

Emerging Trends and Innovations

The evolution of stock management through digital transformation is redefining the tracking, analysis, and optimization of inventory via the integration of developing technology [105]. The Internet of Things (IoT)

has transformed real-time visibility and control; the subsequent phase of progress involves the integration of IoT with Artificial Intelligence, blockchain, edge computing, and digital twin technology. These advances are anticipated to augment automation, decision-making, and operational efficiency in stock and inventory systems [106]. This section examines the most significant future trends influencing innovation in stock management.

Integration of AI and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) are set to become vital components of IoT in stock management. Utilizing the extensive data produced by IoT sensors, smart shelves, and Radio Frequency Identification (RFID) devices, AI facilitates the transition of systems from reactive to predictive and prescriptive operations. Machine learning algorithms can evaluate previous sales trends, seasonal patterns, and external factors such as regional events or weather fluctuations to produce precise demand estimates. This facilitates improved inventory management and mitigates stock-outs and overstocking [107].

Moreover, AI enables real-time anomaly identification, recognizing anomalies or inconsistencies in stock movement that may signify theft, shrinkage, or operational inefficiencies [108]. It also drives intelligent replenishment systems that autonomously create purchase orders when inventory falls below optimal thresholds. Prominent global retailers like Amazon and Zara employ AI to optimize warehousing and shipping, tailor customer experiences, and precisely manage dynamic stocks. As AI advances and gains widespread acceptance, it will enhance forecasting precision and supply chain agility significantly [109].

Blockchain for Transparent Supply Chains

Blockchain technology facilitates decentralized, secure, and immutable record-keeping, hence augmenting confidence and transparency along the supply chain. In stock management, blockchain facilitates the creation of a shared ledger that records and verifies every transaction, movement, and status update of products [110]. This guarantees data integrity and deters tampering, particularly essential in sectors where product authenticity and regulatory compliance are paramount.

The future of stock management shown in Figure 4, is increasingly shaped by technologies like AI for prediction, blockchain for trust and traceability, edge computing for speed, and digital twins for simulation. These tools are paving the way for autonomous, intelligent inventory ecosystems.

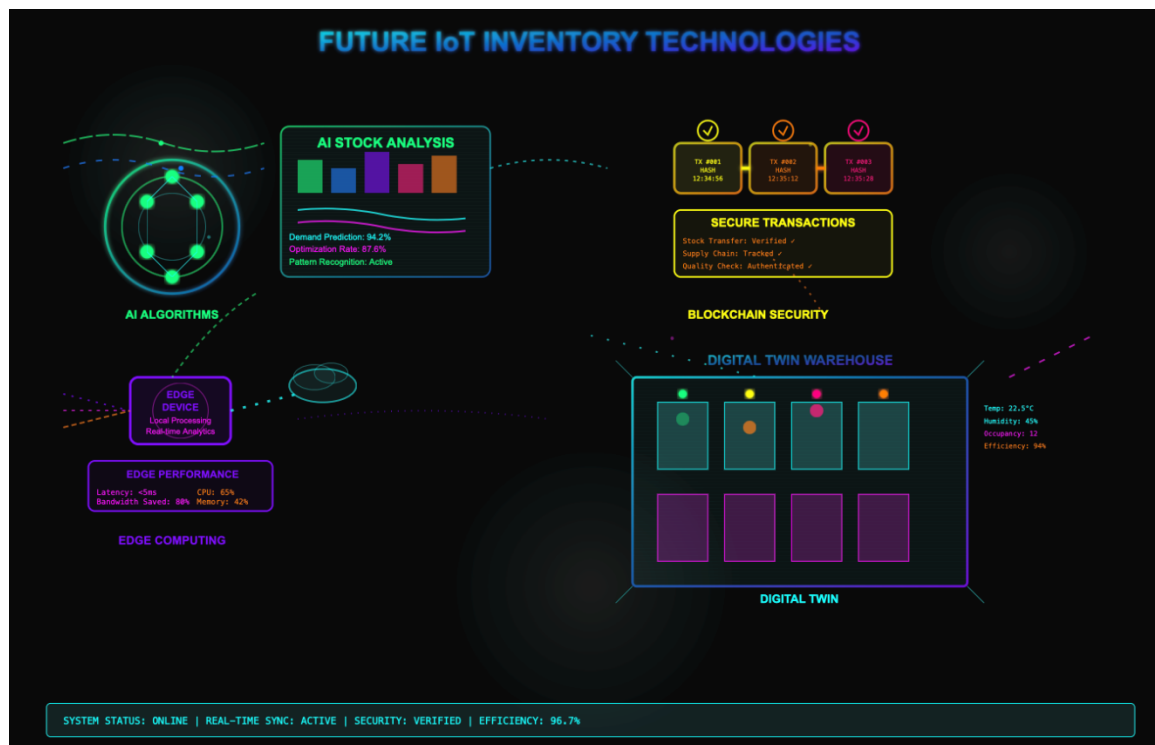


Figure 4: Future-forward technologies transforming IoT-driven stock management: AI, blockchain, edge computing, and digital twins

Luxury firms such as LVMH and Prada have utilized blockchain technology to authenticate high-value products and combat counterfeiting. IBM's Food Trust platform employs blockchain technology to track the progression of food products from farm to table, enhancing traceability and recall efficacy [111]. When integrated with IoT sensors, blockchain can monitor ambient conditions, timestamps, and handling procedures throughout the inventory lifetime, providing comprehensive visibility.

The unalterable characteristics of blockchain render it especially advantageous for auditing and regulatory adherence. It also improves accountability by granting stakeholders, such as suppliers, merchants, and customers, access to authenticated information [112]. As blockchain solutions advance in scalability and integration with corporate systems, they are anticipated to significantly contribute to the development of trust-based, zero-trust inventory ecosystems.

Edge Computing for Accelerated Processing

Edge computing mitigates a significant constraint of cloud-based IoT systems—latency. In conventional designs, data gathered by IoT devices is transmitted to the cloud for processing and decision-making. This process can be laborious and resource-intensive, particularly in situations necessitating prompt response. Edge computing addresses this issue by locally processing data at the network's periphery, via gateways, on-device processors, or edge servers [113].

In inventory management, edge computing facilitates expedited responses to real-time occurrences, including the detection of low stock levels, the identification of misplaced items, and the control of perishable inventory conditions. Local processing enables warehouse robots and intelligent shelves to operate with more autonomy, independent of continuous communication [114]. Corporations such as Walmart have incorporated edge computing into their warehouse operations to expedite inventory selections and enhance customer fulfilment.

Edge computing enhances security, reduces bandwidth costs, and promotes system resilience by minimizing data transmission to the cloud and decreasing dependency on central servers. The adoption of edge

hardware is anticipated to increase in logistics centres, retail shops, and distribution hubs as it becomes more economical and energy-efficient.

Digital Twins in Inventory Simulation

Digital twins are virtual representations that emulate the physical attributes and behaviours of actual systems. A digital twin in stock management can replicate the whole warehouse or retail store, enabling firms to see, monitor, and optimize inventory operations inside a virtual setting [115]. Utilizing real-time data from IoT sensors, these models offer an immediate representation of inventory dynamics, equipment utilization, and spatial efficiency.

Digital twins provide predictive maintenance of machinery, simulation of storage configurations, and optimization of picking routes, thus enhancing operational efficiency. They also enable "what-if" assessments, assisting firms in evaluating scenarios such as abrupt demand increases, supply interruptions, or alterations in layout without interfering with actual operations [116].

Prominent corporations like as Siemens and GE Digital are currently employing digital twin technology in industrial logistics and manufacturing. In retail, digital twins can enhance demand forecasting, customer flow management, and in-store inventory organization [117]. When integrated with AI and edge computing, digital twins transform into formidable instruments for proactive and dynamic inventory management. As technology advances, digital twins are anticipated to become integral elements of intelligent inventory systems, enabling stakeholders to make more informed, data-driven decisions with diminished risk [118].

Findings

The findings of the present study align with prior research that emphasizes the transformative role of IoT in enhancing visibility, efficiency, and automation across supply chains. Similar to earlier works that highlighted RFID-based accuracy improvements [78] and predictive analytics for demand forecasting [34], this study reinforces the importance of integrating IoT with advanced tools such as AI, blockchain, and edge computing to achieve intelligent and agile stock management. While previous literature often focused on individual applications such as cold chain monitoring [37–38] or warehouse automation [41], this work contributes by providing a holistic perspective on how emerging digital technologies collectively shape the future of inventory ecosystems.

Conclusion

The future of inventory management is to incorporate IoT with other sophisticated tools like AI, blockchain, edge computing, and digital twins. These technologies together support intelligent forecasting, real-time decision making, supply chain visibility, and optimization through simulation which allows companies to build more efficient and resilient systems. This study has limitations, however. As a literature-based review, it does not have empirical focus and it may also be quickly outdated due to rapid technological change. In practice, organizations need to balance the costs of investment and implementation with the cybersecurity risks and the difficulties of integrating multiple systems. Theoretical research could further be focused on interoperability standards, architecture suitable for scale, and how emerging technologies can work in combination to enhance supply chain resilience. Addressing these issues would help to bring the potential into practice.

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RESEARCH ARTICLE

Effectiveness of guided imagery in terms of cancer pain and perceived stress among patients with cancer

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Abstract: *Background:* The World Health Organisation (WHO) reports that cancer accounts for 13% of global deaths. For cancer survivors, pain and stress significantly debilitate their quality of life, interfering with daily activities and the healing process. While the negative impact of these symptoms is well-documented, there is limited research on the effectiveness of non-pharmacological interventions in the Indian context. *Aim:* This study aimed to evaluate the effectiveness of a guided imagery intervention in reducing cancer-related pain and perceived stress among Stage II cancer patients receiving radiation therapy at a cancer institute in Trichy. *Methods:* A pre-experimental study with a pre-test and post-test design was conducted using a convenience sample of 30 patients. Each patient received a 15-minute guided imagery session with music daily for one week. Pain and perceived stress were measured using the Pain Numerical Scale and the Perceived Stress Scale, respectively, on the 7th day following the intervention. *Results:* Before the intervention, the sample reported mild to moderate pain (63.3% mild, 36.6% moderate) and a high prevalence of severe stress (80%). After one week of intervention, a notable improvement was observed, with 100% of patients reporting mild pain and the percentage of patients with severe stress decreasing to 60%. Paired t-tests showed a statistically significant reduction in both pain ($t=11.21$, $p<0.01$) and perceived stress ($t=7.14$, $p<0.05$) levels, indicating the guided imagery was effective. *Conclusion:* The findings suggest that guided imagery is an effective and viable non-pharmacological intervention for reducing pain and perceived stress in cancer patients. This highlights the potential for integrating guided imagery into standard care protocols to improve patient outcomes and overall quality of life.

Keywords: Guided imagery, Cancer, Pain, Stress

Background

According to the latest GLOBCAN 2022 report by Singh et al., India recorded approximately 1.41 million new cancer cases and 0.92 million cancer deaths in 2022, accounting for about 12% of the global total. The report identified key cancers in males as respiratory, prostate, and colorectal, while breast, cervical, and ovarian cancers were most common in females [1]. The Ministry of Health and Family Welfare projects a continued rise in cancer cases, with the Indian Council of Medical Research (ICMR) reporting over 1.5 million cases in 2024, highlighting cancer as a critical public health challenge in the country [2].

Cancer patients experience a wide array of physical and psychological symptoms that significantly impact their quality of life. Among these, pain and stress are highly prevalent and are known to interfere with daily activities and the overall healing process [3]. Guided imagery is a therapeutic technique that uses pleasant mental visualisation to improve a patient's mood and well-being. It is a form of guided meditation or mental health therapy, similar to cognitive behavioural therapy (CBT) with a guided self-help component [4]. The

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Received: 07/08/25, Accepted: 29/09/25, Published Online: 07/10/25

process involves a researcher or therapist guiding a patient through simple visualisation and relaxation steps, using imagery to help them consciously divert their mind from sensations of pain and stress [5].

This mind-body technique is widely used in cancer care and has been proven effective in various situations [5,6]. Research has shown that positive mental imagery can promote relaxation and reduce stress [6], improve mood [7], alleviate pain (8,9), boost the immune system [10] and minimise nausea and vomiting [11]. Given the existing treatment burden, there is a growing need to explore natural and supportive measures to improve patient well-being.[4] .And there is limited evidence-based practice in the Indian set-up, hence this study aims to investigate a non-pharmacological intervention—guided imagery—to assess its effectiveness in managing pain and stress among cancer patients.

The goal of this study is to assess the effects of guided imagery on patients with cancer. The first objective was to assess cancer pain and perceived stress before and after administering guided imagery. Second, the study seeks to establish the relationship between cancer pain and perceived stress before and after guided imagery. The third objective was to determine the association between selected clinical variables, cancer pain, and perceived stress.

Materials and methods

Study Design and Setting

This study employed a one-group pre-test and post-test design to evaluate the immediate and sustained effect of a guided imagery intervention on cancer pain and perceived stress. The study was conducted at a secondary-level, 100-bedded cancer institute in Trichy, India. Data collection occurred over a period of three months.

Participants and Sampling

A convenience sample of patients diagnosed with Stage 2 cancer was recruited. The inclusion criteria required patients to be: aged 18 years or older, able to understand Tamil or English, currently admitted to the hospital, able to perform self-care activities and ambulate, and experiencing baseline pain of ≥ 3 on the 0-10 Numerical Pain Rating Scale (NPRS) with concurrent mild perceived stress. The threshold of ≥ 3 on the NPRS and mild stress was chosen to ensure sufficient variability for detecting changes following the intervention, as recommended by Farrar et al. [12]. Exclusion criteria included patients with Stage 4 cancer, those receiving palliative care, or those currently on intravenous analgesics or morphine medication.

Of the fifty eligible patients identified, thirty consented to participate. Reasons for non-participation included fatigue, unsure regarding the relaxation technique's effectiveness, short hospital admission time, being too stressed and incomplete post intervention questionnaire, resulting in a final sample size of $n=30$ for the analysis.

Intervention

The intervention consisted of a 15-minute audiotaped guided imagery session developed by the investigator following a literature review and with the assistance of a yoga teacher. The tape featured guided instruction set to music and included a pleasant waterfall scene and sounds [5]. The tape was validated for content by three experts: a cancer specialist, a nursing professor, and a yoga teacher. Usability and feasibility were assessed through pre-testing with two patients. All participants used the same audiotape.

Procedure and Data Collection

Baseline data (pre-test) for pain and perceived stress were collected on Day 1 immediately prior to the administration of the guided imagery tape. Participants listened to the audiotape once a day for next seven days. Thier practice of guided imagery was also noted. Post-test data were collected seven days later, on Day 7.

Instruments

Two instruments were used to collect data: 1) Pain Numerical Rating Scale (NPRS): Pain intensity was measured using a standardised NPRS [13,14]. This 11-point scale (ranging from 0 = No Pain to 10 = Worst Pain Imaginable) was administered verbally. 2) Perceived Stress Scale (PSS-10): Perceived stress was measured using the 10-item Perceived Stress Scale (PSS-10), developed by Cohen et al. from Carnegie Mellon University [15,16]. The PSS-10 assesses the degree to which situations in one's life are appraised as stressful, with responses rated on a 5-point Likert scale (0=never to 4=very often). Scores were calculated by reversing the scores of the four positive items (items 4, 5, 7, and 8) and summing all 10 items. Formal permission was obtained for the use of both standardised scales.

Ethical Considerations

The study protocol received approval from the Institutional Ethics Committee, and formal authorization was obtained from the hospital administration. All participants were thoroughly briefed on the study's objectives and provided written informed consent prior to enrollment.

Data Analysis Plan

Data were coded, tabulated, and analysed using SPSS software, Version 19.0 (IBM Corporation). Both descriptive statistics (e.g., frequencies, means, standard deviations) and inferential statistics (e.g., paired t-tests, correlations) were used to address the study objectives.

Results

Sociodemographic and clinical data

The study included 30 participants, with an equal distribution of males and females (50% each). The majority of the sample were middle-aged, with 46.6% of participants being between 40 and 50 years old. All participants were married, and 93.3% resided in urban areas. Over half of the participants (53.3%) lived in a joint family.

Regarding educational background, 73.3% of the participants had a secondary or higher secondary level of education. The most common monthly income was between ₹5,000 and ₹10,000, reported by 43.3% of the sample. Occupations were varied, with the most common being housewives (36.6%), followed by government and private employees (20% each).

Clinical characteristics revealed that 86.6% of participants reported engaging in both tobacco use and smoking. The most common site of cancer was the gastrointestinal (GI) system (56.6%), and the majority of patients (73.3%) had been undergoing treatment for less than six months. The demographic and clinical characteristics are detailed in Table 1.

The study findings are presented according to the established research objectives. The results are based on the analysis of data collected from the final sample of 30 sample (N=28).

Table 1: Demographic characteristics

S.No	Demographic variables	N=30	%
1	Age		
	30-40 years	5	16.6
	40-50 years	14	46.6
	50-60 years	11	36.6
2	Sex		
	Male	15	50
	Female	15	50
3	Marital status		
	Married	30	100
	Unmarried /single		
4	Education		
	Secondary	10	33.3

S.No	Demographic variables	N=30	%
	Higher secondary	12	40
	Graduate	8	26.6
5	<i>Residence</i>		
	Urban	28	93.3
	Rural	2	6.6
6	<i>Type of family</i>		
	Joint family	16	53.3
	Nuclear family	14	46.6
7	<i>Income</i>		
	5,000- 10,000	13	43.3
	10,001-20,000	6	20
	< 20,000	11	36.6
8	<i>Occupation</i>		
	House wife	11	36.6
	Government employee	6	20
	Private employee	6	20
	Labourer	2	6.6
	Retired	5	16.6
9	<i>Tobacco use</i>		
	Yes	26	86.6
	No	4	13.3
10	<i>Smoking</i>		
	Yes	26	86.6
	No	4	13.3
11	<i>Duration of treatment</i>		
	0-6 months	22	73.3
	6-12 months	5	16.6
	< 12 months	3	10
12	<i>Site of cancer</i>		
	Breast cancer	8	26.6
	GI system cancer	17	56.6
	GU system cancer	4	13.3
	Respiratory cancer	1	3.3

Effect of guided imagery on cancer pain and perceived stress

The first objective was to determine the level of cancer pain and perceived stress before and after the guided imagery intervention. The results of the paired t-test indicated that the guided imagery intervention was highly effective in significantly reducing both cancer pain and perceived stress levels among the participants (Table 2).

Cancer Pain Reduction

The mean cancer pain score, measured using the Numerical Pain Rating Scale (NPRS), significantly decreased from a pre-intervention mean of 4.5 to a post-intervention mean of 3.6 ($t=11.217$, $p<.05$). This reduction demonstrates the immediate efficacy of the guided imagery in pain management.

Perceived Stress Reduction

Similarly, the mean perceived stress score showed a highly significant drop. The mean score decreased from 10.66 at pre-test to a post-test mean of 2.4 ($t=7.14$, $p<.05$).

Table 2: Effectiveness of guided imagery on cancer pain and perceived stress

Variables	Range	Pretest	Mean	Post test	Mean	SD	Paired t test
Cancer pain	Mild	19(63.3%)	4.5	30(100%)	3.6	0.521	11.217* $p<0.01$
	Moderate	11 (36.6%)					
	Severe	-					
	Mild	-	-	-	-	-	7.14*

Variables	Range	Pretest	Mean	Post test	Mean	SD	Paired t test
Perceived stress	Moderate	6(20%)	5.4	12(40%)	10.66	2.4	p<0.05
	Severe	24 (80%)		18 (60%)			

Relationship between cancer pain and perceived stress

The second objective was to examine the relationship between cancer pain and perceived stress before and after the intervention. Pearson correlation coefficients revealed a strong positive linear relationship between the two variables at both time points. Before the guided imagery was administered, a strong positive correlation was found ($r=0.8$). This indicates that higher levels of cancer pain were associated with higher levels of perceived stress. Following the intervention, the correlation remained strong, though slightly diminished, at $r=0.7$. The persistent positive relationship suggests that despite the overall reduction in both symptoms, their interdependence was maintained. Participant compliance with the full 15-minute guided imagery session was 72%. Non-compliant subjects cited fatigue and lack of concentration as the primary reasons for not completing the full session.

Association with selected clinical variables

The final objective was to determine the association between selected clinical variables (site of cancer, duration of treatment) and the outcome variables (cancer pain and perceived stress).

Pre-Intervention Associations

A Chi-square test of independence was performed using pre-intervention data. The results showed no statistically significant association between the site of cancer and the severity of perceived stress ($\chi^2(3)=5.99$, $p>.05$). Likewise, there was no statistically significant association between the duration of treatment and the severity of cancer pain ($\chi^2(2)=3.99$, $p>.05$). This suggests that baseline pain and stress levels were independent of these two clinical factors.

Post-Intervention Limitation

It was not possible to reliably establish the association between the selected clinical variables and the post-test results for cancer pain. This was due to a ceiling effect in the data, where all patients (100%) reported a mild pain level after the intervention, which resulted in a lack of variability in the post-test pain scores. This uniform outcome made further meaningful statistical association analysis on the post-test pain data impossible.

Table 3 The association between perceived stress with selected clinical variables.

Sl No	Clinical variables	Mild	Moderate	Severe	X ²
1	Site of cancer				$\chi^2(3, N=30) = 5.99, p>.05$
	Breast cancer	-	4	4	
	GI system	-	3	14	
	GU system	-	2	2	
	Respiratory cancer	-	1	0	
2	Duration of treatment	-			$\chi^2(3, N=30) = 5.99, p>.05$
	0-6 months	-	9	13	
	6-12 months	-	2	3	
	<12 months		2	1	

Discussion

This study aimed to evaluate the effectiveness of an audiotaped guided imagery intervention in reducing cancer pain and perceived stress among patients with Stage II cancer.

The demographic data from this study align with broader epidemiological trends. The sample showed an equal distribution of cancer among males and females, which is consistent with the GLOBOCAN 2022 report showing a similar overall cancer incidence rate between the sexes globally[1]. The prevalence of gastrointestinal cancer in the study sample (56.6%) is also consistent with global data, as colorectal and

gastric cancers are among the most common forms of cancer worldwide [1]. The high rate of tobacco use and smoking (86.6%) found in the participants is a notable finding, as these habits are known to be significant risk factors for various types of cancer.

Our findings support the use of guided imagery as a non-pharmacological intervention for symptom management in oncology. The study demonstrated a statistically significant reduction in both cancer pain [19] and perceived stress levels following the intervention. The mean perceived stress score dropped from 10.66 to 2.4 ($t=7.14, p<.05$). This is consistent with previous research by Chandreabulous et al. (2020) and Mahdizadeh et al. (2019), who also found that guided imagery and other mind-body techniques were effective in reducing anxiety and depression in cancer patients [17,18]. Similarly, the significant reduction in pain scores from 4.5 to 3.6 ($t=11.217, p<.05$) aligns with findings from De Paolis et al. (2020), who showed that guided imagery effectively alleviated pain and symptom distress in terminal cancer patients[20].

The analysis of clinical variables revealed no significant association between the site of cancer or the duration of treatment and the initial level of pain or stress. However, it's worth noting that after the intervention, all participants reported a mild pain level (100%). This lack of variability in the post-test data prevented a meaningful association analysis between these clinical variables and the post-intervention outcomes. This suggests the guided imagery intervention was effective across all cancer sites and treatment durations.

The study also highlighted several factors that may influence the effectiveness of guided imagery, such as patient compliance and the intervention's external validity. The compliance rate was 72%, with patients reporting fatigue and difficulty concentrating. This suggests that while guided imagery can be highly effective, its success is dependent on the patient's willingness and ability to practice the technique. The patient's environment, level of self-practice, and personal concentration may also influence the outcome.

The primary limitation of this study was the small sample size and the absence of a control group, which limits the ability to rule out other factors that may have contributed to the observed changes. The challenges in recruiting patients and the reported patient fatigue and medication timing affecting intervention adherence were also notable limitations. The inconsistency in using patient journals for data collection, although providing quantitative data, introduced potential for bias.

Conclusion

This study successfully demonstrated that the guided imagery intervention significantly reduced both cancer pain and perceived stress in patients with Stage 2 cancer. Findings support the use of guided imagery as an effective, non-pharmacological adjunct therapy for symptom management.

The findings of this study provide compelling evidence that the guided imagery intervention is an effective, non-pharmacological strategy for significantly reducing both cancer pain and perceived stress in patients with Stage 2 cancer. While the intervention proved beneficial, its one-group design and the small sample size limit the ability to generalize the results. Future research should address these limitations by incorporating a randomized controlled trial (RCT) design with a larger sample to strengthen the evidence base. Additionally, future studies could benefit from focusing on a single cancer site to better understand site-specific pain responses. Based on these positive outcomes, it is recommended that guided imagery be integrated into routine oncology care, with training provided to nursing staff to facilitate its consistent administration.

Acknowledgements

The author extends sincere gratitude to the patients who participated in this study, as well as to the institute and hospital for granting permission to conduct the research.

Funding

This research received no external funding.

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REVIEW ARTICLE

Exploring the potential of adaptive computing architectures in building efficient infrastructure systems for artificial intelligence

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Abstract: The accelerating demands of artificial intelligence workloads necessitates a paradigm shift in computing infrastructure, moving beyond traditional static and monolithic architectures towards more dynamic and adaptive solutions. This research delves into the potential of adaptive computing architectures to address the increasing computational requirements of AI, focusing on how these architectures can optimize resource utilization, enhance performance, and reduce operational costs by dynamically reconfiguring hardware resources to match the specific needs of AI algorithms, adaptive computing offers a compelling alternative to fixed hardware platforms, promising significant improvements in efficiency and scalability. This paper explores various adaptive computing technologies, including Edge AI, field-programmable gate arrays (FPGA), configurable system-on-chips, and software-defined hardware, analyzing their strengths and weaknesses in the context of AI applications. Further, explored the impact of adaptive computing on key AI domains such as deep learning, machine vision, and natural language processing, highlighting the significance of potential for customized hardware acceleration, and auto scaling resources to meet data processing, availability, provisioning of resources to unlock new levels of performance and energy efficiency and provides a comprehensive overview of the challenges and opportunities associated with deploying adaptive computing in AI infrastructure, offering insights into future research directions and practical considerations for adoption.

Keywords: Artificial Intelligence, Enterprise infrastructure systems, Computing architecture, Adaptive computing

Introduction

The rapid increase of artificial intelligence and its subset solutions such as machine learning, deep learning, adoption across diverse industry sectors has provoked an unmatched demand for computational resources, requiring the development of efficient and scalable AI infrastructure [1].

The traditional computing architectures, more often depicted by their static and homogeneous nature, and are increasingly strained by the dynamic and heterogeneous demands of modern AI workloads [2].

Adaptive computing architectures, distinguished by their ability to dynamically reconfigure their hardware and software resources in response to changing application requirements, offer a promising solution to address these challenges [3].

These architectures are capable of optimizing resource allocation, enhancing performance, and improving energy efficiency across a wide spectrum of AI applications, ranging from deep learning and machine learning to computer vision and natural language processing [4].

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Received: 26/07/25, Accepted: 29/09/25, Published Online: 07/10/25

The inherent flexibility of adaptive computing allows for the creation of systems that can operate effectively in resource-constrained environments, which is particularly relevant in edge computing scenarios and military applications where timely and precise decision-making are paramount [5]. By dynamically adjusting the hardware and software configurations, these architectures can cater to the specific needs of AI algorithms, leading to substantial improvements in computational speed and energy consumption [6].

Further, the adaptability of these systems facilitates the integration of novel AI algorithms and techniques, ensuring that the infrastructure remains relevant and efficient over time. The development of adaptive computing architecture necessitates a holistic approach, encompassing advancements in hardware design, software orchestration, and AI algorithm optimization. This exploration delves into the potential of adaptive computing architectures in constructing efficient AI infrastructure and systems, examining their underlying principles, key technologies, and potential applications.

Adaptive Computing for Enhanced AI Efficiency

The adaptive computing architectures hold immense potential for transforming AI infrastructure by providing the flexibility and efficiency required to address the evolving demands of AI workloads [7]. These architectures dynamically adjust their hardware and software resources to optimize performance, power consumption, and resource utilization, adapting to the specific needs of different AI tasks [8]. This adaptability is crucial in handling the diversity of AI algorithms and datasets, allowing for tailored solutions that maximize efficiency.

For example, in edge computing scenarios, where resources are limited and energy efficiency is paramount, adaptive computing can enable the deployment of complex AI models by dynamically optimizing the hardware configuration to match the computational requirements of the specific task [9], [10].

Adaptive learning systems, which tailor educational content and delivery methods to individual learner needs to exemplify the potential of AI to personalize and optimize experiences [11]. Moreover, adaptive computing can facilitate the integration of emerging AI techniques, such as neuromorphic computing and quantum computing, into existing AI infrastructure, enabling the development of more powerful and efficient AI systems [12].

The development of these architectures requires a multifaceted approach, considering hardware design, software orchestration, and AI algorithm optimization, and by dynamically adjusting hardware and software configurations, adaptive computing architectures can cater to the specific needs of AI algorithms, resulting in significant improvements in computational speed and energy consumption [13].

Edge Computing for AI

The emergence of edge AI, driven by advancements in AI efficiency and the proliferation of various Internet of Things devices, highlights the critical importance of adaptive computing in enabling real-time data management, processing, analysis and distribution of the edge network [14], [15].

The computational gap between resource-intensive deep learning algorithms and resource-constrained edge systems poses a significant challenge in edge intelligence [6]. The use of AI at the edge facilitates a multitude of applications, spanning from autonomous systems and human-machine interactions to IoT and beyond, capitalizing on the advantages of both edge and cloud computing [8].

Edge computing addresses the challenges of latency, bandwidth, and autonomy by processing data closer to the source of generation [16]. This paradigm reduces the need to transfer vast amounts of data to centralized cloud servers, minimizing latency and enabling real-time decision-making [15].

The edge computing augments data privacy and security by retaining the sensitive data within the chosen local network, and reduces the risk of unauthorized access, that include permission & privileges elevation and the data breaches. The design of lightweight deep neural networks to reduce the number of floating-point operations and parameters for execution on edge devices has become increasingly important [17], [18].

The edge computing for AI involves works based on certain permutations and computations, therefore the nearby users data gets cached at the network's edge location, versus instead of centralized location like colocation datacenter or the cloud service provider data center [19], [20]. Edge AI systems should also include mechanisms for continuous learning and adaptation, enabling them to improve their performance and accuracy over time [21]. The edge network typically comprises of many numbers of highly distributed and connected systems that are purposed for data collection & processing, analysis and caching to the nearest locations which are close to where the data is originally stored and managed [4].

Research Gaps

Although adaptive and edge computing presents numerous opportunities yet several research gaps exists and it must be addressed to fully realize its potential, such as developing energy-efficient AI algorithms and hardware architectures that can operate within the enhanced power budgets of edge devices is crucial [22], current edge AI systems often lack the ability to handle dynamic and unpredictable changes in the environment, which can degrade their performance and reliability [23], more research is needed to develop robust and adaptive edge AI systems that can handle unexpected events and maintain their accuracy and performance in dynamic environments [24], [25].

The need for specialized hardware to accelerate AI workloads on edge devices is also a major area of focus [26]. It is also essential to address the challenges related to data privacy and security in edge AI deployments, as edge devices are often deployed in unsecured environments and can be vulnerable to cyberattacks [27]. There is need to investigate how to effectively partition and distribute AI models across multiple edge devices, while minimizing communication overhead and ensuring data consistency [28]. The development of specialized hardware accelerators, such as GPUs, FPGAs, and ASICs, has played a crucial role in accelerating AI workloads [29], [30].

Challenges

Despite the significant potential of adaptive computing architectures in AI, several challenges remain that need to be addressed to fully realize their benefits and to enable their widespread adoption in AI infrastructure and systems. One of the major challenge is the complexity of designing and implementing these architectures, which requires expertise in hardware design, software engineering, and AI algorithm optimization [23].

The development of efficient and scalable software tools and frameworks for managing and orchestrating adaptive computing resources is crucial for simplifying the deployment and management of AI applications on these platforms. Another challenge is the need for standardized interfaces and protocols to facilitate interoperability between different adaptive computing components and platforms [31].

Further, ensuring the security and reliability of adaptive computing architectures is vital importance, as the systems are often deployed in critical applications where failures can bring significant and uneventful consequences [32]. The development of unique hardware technologies, such as neuromorphic computing and quantum computing, could further enhance the capabilities of adaptive computing architectures for AI.

Developing efficient and automated design tools that can translate high-level AI algorithms into optimized hardware configurations for adaptive computing architectures is crucial [33]. Furthermore, ensuring the security and reliability of adaptive computing systems is essential, as they are often deployed in critical applications where failures can have significant consequences. There is a huge problem of noisy and unlabeled data in heterogeneous platforms [3].

Furthermore, challenges from a company perspective can include: security, budget, lack of talent to implement and run AI, big data and data analytics, integration with existing systems, and procurement limitations [34].

One of the significant challenges is the lack of standardized programming models and software tools for adaptive computing architectures, which can hinder the development and deployment of AI applications on these platforms [35]. A standard programming model can significantly reduce the complexity of developing AI applications on adaptive computing architectures and facilitate code portability across different platforms.

Potential Applications

AI has a vast potential to be extremely helpful in manufacturing, especially in applications like predictive maintenance, quality assurance, and process optimization [36]. The integration of AI into manufacturing operations can lead to significant cost and efficiency benefits, especially when combined with edge computing and fog computing paradigms [1].

Adaptive computing architectures hold immense potential for revolutionizing AI infrastructure and systems across various domains. The convergence of technologies like the Internet of Things, AI, edge-fog-cloud computing, and block chain is driving digital transformation, opening doors for innovative applications in diverse sectors such as healthcare, finance, and industry 4.0 and many more [32].

Integrating AI technologies into existing systems is difficult due to a lack of understanding about what a particular type of AI technology can or cannot do [37]. Thus, the adaptive solutions must be integral to developing resilient, and scalable systems, aiding to the wider adoption of sustainability measures in the physical infrastructures such as data center and as well as digital eco system.

Findings

Adaptive computing allows direct stacking and provisioning of compute, storage, and acceleration resources, largely fostering the infrastructure utilization and minimizing idle hardware. This adaptable approach leads to the resource optimization by avoiding the allocation of static capacity in servers, enabling tailored and dynamic configuration for each application [38].

Data processing and availability requires an improved performance and latency, such as navigating the computation resources to make available the data sources, using adaptive platform solutions such as edge networks, FPGA, reduces latency distinctively and the network bottlenecks [39], especially on data intensive and sensitive operation's to real-time capacity and performance efficiency demands like streaming.

Applications and systems that are built on adaptive architectures could be reconfigured or upgraded in relevance to varying workload requirements without the need for onboarding immersive hardware, promoting scalability and future ready [40].

The architectures & application solutions that are built with artificial intelligence and provisioning of resources could be converted to imitation of human-centric technology systems [39], therefore, by assisting with the dependability, adaptability and robustness of critical infrastructure in domains like banking, finance, energy, healthcare, and FMCG.

Opportunities and Future Directions

As AI continues to permeate various aspects of modern life, the computational demands of AI models are growing exponentially. Adaptive computing architectures offer a promising solution to address the evolving demands of AI, as they can dynamically adjust their hardware resources and configurations to optimize performance for different AI tasks [30]. By dynamically mapping computational tasks to the most suitable hardware resources, adaptive computing architectures can achieve significant performance gains while reducing energy consumption and improving resource utilization. In advanced manufacturing, AI techniques are used to address unique manufacturing problems in order to significantly improve productivity, quality, flexibility, safety, and cost [41]. Also, the convergence of AI and Fog Continuum presents a massive opportunity for research and enterprise [25]. The new intelligent applications are feasible due to fog computing, which provides computing capabilities closer to edge devices, enabling new applications and services [42].

The convergence of adaptive computing and AI holds immense promise for creating intelligent systems that can learn, adapt, and evolve in response to changing environments and demands, and the integration of AI into edge devices is expected to grow significantly in the near future [43]. Overcoming these challenges will require collaborative efforts from researchers, engineers, and industry stakeholders to develop innovative solutions and standards that pave the way for the widespread adoption of adaptive computing architectures in AI infrastructure. Also, the development of a unified data model is needed at the edge nodes, as the data belongs to different subsystems [44]. The goal is to leverage the strengths of both cloud and edge computing paradigms to enable a wide range of AI applications with stringent latency, bandwidth, and privacy requirements [5]. By strategically allocating computational tasks between edge and cloud resources, the hybrid approach optimizes overall system performance while adhering to application-specific constraints. Also, edge AI systems should also include mechanisms for continuous learning and adaptation, enabling them to improve their performance and accuracy over time.

Further research is essential and should focus on developing robust encapsulation layer, micro-services (i.e., kubernetes), AI-driven, event-driven sustainable architecture [45], automated provisioning and optimization methods, to make adaptive computing accessible to architects, developers, and across the enterprises.

Discussion

Despite major advancement on the hardware platforms, software applications and tools, the encapsulation layer to fully utilize adaptive infrastructure remain a bottleneck [46], this the intelligence aware automated deployments, and effective compiler solutions are critical for mainstream.

The adaptive computing's principles should be applied across the industry and affiliated domains, to effectively address the uncertainties, resilience, and to the advancement of sustainable practices and future solutions such as AI/ML for DevOps must be engaged [47].

The adaptive architectures are dynamic in nature, which highlights the significance of blended hardware & software designs [48], cultivating the communication efficiently between the varying hardware and software components, which reinforces innovation in design methodologies and system architecture paradigms.

Implications

The adaptive computing architectures offers several theoretical and practical implications for the advancement of efficient infrastructure and some of these are listed in this section.

Theoretical Implications

Redefining architecture boundaries - The emergence of modern adaptive architecture, challenges the traditional disassociation between hardware and software, prompting for a re-assessment of their interrelation [49].

Observability metrics and paradigms – Instead prioritizing decisions based on performance metrics, the adaptive architectures spotlights for a comprehensive viewpoints, such as introducing new metrics – performance, energy efficiency, availability, reliability, and security first approach as core design principles [25].

This prompts for a new and enhanced research on contemporary areas, such as reconsidering the von Neumann model [33] and devising flexible interfaces that allow for dynamic, application-aware configuration.

Practical Implications

Dynamic resource allocation: The adaptive computing empowers real-time provisioning, with that the infrastructure can scale the resources elastically based on demand without involving any intervention. This greatly improvises the efficiency, cost effectiveness, and agreed SLA (service-level) for cloud platforms, edge devices, and deployments [39].

Energy and performance efficiency – The adaptive computing reduces both latency and power consumption, when the systems are configured to auto-scale the resources capacity such as compute and memory, which is an essential for the data intensive operations [44].

Security and Reliability - Infusing the security first approach and resilience at the core of architecture level will be more relevant to design infrastructure which would dynamically respond to threats, failures, thus enhancing the security and resilience of critical systems [51].

Conclusion

As AI models become more complex and datasets continue to grow, the very need for specialized hardware accelerators has become increasingly apparent, with that the adaptive computing architectures offer a promising approach to building efficient AI infrastructure and systems, with the potential to significantly improve performance, reduce latency, and lower energy consumption for a wide range of AI applications by dynamically auto scaling the hardware resources through configurations to match the specific needs of each AI requirements, the adaptive architectures could very well overcome the limitations of standard CPU and GPU based systems [30].

The design and implementation of adaptive computing systems can be complex and require specialized expertise in hardware and software development.

The development of efficient and scalable programming models and tools for adaptive computing architectures is also essential to enable developers to easily create and deploy AI applications. AI technologies have witnessed exponential growth in recent years, driven by advancements in machine learning, particularly deep learning. However, implementing AI models on edge devices may cause considerable trials and encounters due to the inadequacy in available resources.

The trade-offs between adaptive computing architectures and traditional systems, showing that adaptive architectures are particularly well-suited for applications that require high performance, low latency, and energy efficiency yet time and again look out for opportunities to improvise [51] and thus, the arising key challenges must be addressed to fully realize the potential of adaptive computing architectures in building efficient AI infrastructure and systems.

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