American Journal of
Biomedical Science & Research

www.biomedgrid.com
ISSN: 2642-1747

Case Report

Internet of Things and Intelligent Data Analytics in Clinical Medicine

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To Cite This article: *Ibrahim H Osman and Soha Maad*. Internet of Things and Intelligent Data Analytics in Clinical Medicine. Am J Biomed Sci & Res. 2026 31(2) AJBSR.MS.ID.004017,* **DOI:** 10.34297/AJBSR.2026.31.004017

Received: May 07, 2026; **Published:** May 14, 2026

Abstract

Internet of Things and Artificial Intelligence are penetrating various application domains. The objective of this paper is to present a clinical medicine case study that leverage the combined use of Internet of Things (IoT), Agentic Artificial Intelligence (AI) and Data Envelopment Analysis. The paper overviews the evolution and widespread use in various application domains of Internet of Things, Agentic Artificial Intelligence and Data Envelopment Analysis (DEA). A SWOT (Strength, Weakness, Opportunities, Threats) analysis is conducted to assess the use and penetration of Internet of Things, Agentic Artificial Intelligence and Data Envelopment Analysis (DEA) in various application domains. Following this overview, the paper considers a clinical medicine case study and the combined use and potential of Internet of Things (IoT), Agentic Artificial Intelligence (AI) and Data Envelopment Analysis to enhance medical decisions based on clinical medicine data. The case study reveals that the combined use of Internet of Things (IoT), Agentic Artificial Intelligence (AI) and Data Envelopment Analysis has a growing potential in clinical medicine. These emerging technologies and analytical models will largely shape in the future decision making based on clinical medicine data.

Keywords: Internet of things, Agentic artificial intelligence, Data envelopment analysis, Clinical medicine, Case study, Decision making, SWOT Analysis

Introduction

The Internet of Things IoT holds significant potential in various domains. The Internet of Things (IoT) represents a paradigm in digital transformation where everyday objects are embedded with sensors, software, and connectivity to collect and exchange data. This interconnected ecosystem holds significant potential across diverse domains, enabling automation, efficiency, and real-time decision-making. In healthcare, IoT devices such as wearable sensors and remote monitoring systems allow continuous tracking of patient health, improving diagnostic accuracy and enabling personalized treatment. These technologies also support telemedicine, bridging gaps in access to medical expertise for remote populations [12]. In the context of smart cities, IoT provides the backbone for intelligent infrastructure management. Connected traffic systems, smart parking, and waste management solutions reduce congestion and optimize resource allocation. IoT also enhances public safety through surveillance and disaster response networks, while integration with big data analytics allows municipalities to make evidence-based decisions that improve sustainability and urban living standards [5]. Industrial applications of IoT, often referred to as the Industrial Internet of Things (IIoT), are central to the evolution of Industry 4.0. By embedding sensors in machinery, manufacturers can implement predictive maintenance, reducing downtime and operational costs. Real-time monitoring of production processes enhances efficiency and supports the development of smart factories. Similarly, in agriculture, IoT enables precision farming by monitoring soil conditions, crop health, and livestock, allowing farmers to optimize resource use and increase yields while promoting sustainability [12].

Energy and environmental management also benefit from IoT integration. Smart grids balance supply and demand more effectively, while connected meters empower consumers to monitor and reduce energy consumption. Environmental monitoring systems track air quality, water pollution, and climate variables, providing critical data for sustainability initiatives and policy-making. Despite these advances, IoT faces challenges related to security vulnerabilities, data privacy, interoperability, and scalability. Addressing these issues through standardized protocols and governance frameworks is essential to fully realize IoT's transformative potential [5]. Moreover, Agentic Artificial Intelligence (AI) has a rising potential in various domains. Agentic Artificial Intelligence (AI) is emerging as a transformative paradigm in the evolution of intelligent systems, characterized by its capacity to act autonomously, pursue goals, and adapt dynamically to changing environments. Unlike traditional AI, which is largely reactive and dependent on predefined instructions, agentic AI emphasizes agency which is the ability of systems to plan, reflect, and orchestrate actions in pursuit of objectives. This shift positions agentic AI as a cornerstone of next-generation applications across healthcare, finance, robotics, and governance, where proactive and context-aware decision-making is increasingly essential [9]. In healthcare, agentic AI demonstrates rising potential by supporting clinical decision-making through autonomous analysis of patient data, continuous monitoring, and adaptive treatment recommendations. Its ability to integrate symbolic reasoning with generative models ensures both safety and flexibility, making it suitable for sensitive domains where reliability is paramount. Similarly, in finance, agentic AI enables adaptive trading strategies, fraud detection, and customer service automation by learning from dynamic market signals and orchestrating complex workflows. These applications highlight the system's ability to move beyond static algorithms toward proactive engagement with real-world complexity [1].

Robotics is another domain where agentic AI is proving indispensable. Autonomous agents equipped with planning and reflection capabilities can navigate environments, collaborate with humans, and execute tasks with minimal supervision. This enhances the potential for human–robot interaction in industrial, domestic, and exploratory contexts. At the same time, governance and policy-making are beginning to explore agentic AI for decision support, though ethical considerations regarding accountability, transparency, and alignment with human values remain pressing. Scholars argue that hybrid neuro-symbolic approaches may provide a pathway to balance adaptability with safety, ensuring trustworthy deployment in critical sectors [2]. Despite its promise, agentic AI faces challenges that must be addressed to unlock its full potential. These include the absence of standardized evaluation metrics, risks of misaligned goals, and vulnerabilities in multi-agent coordination. Ethical and governance frameworks are urgently needed to regulate its deployment, particularly in domains where autonomous decisions carry significant societal impact. As research advances, agentic AI is increasingly viewed not only as a technological innovation but also as a socio-technical system requiring careful integration into existing structures of accountability and trust [2]. Data Envelopment Analysis a data analytical model that can be implemented using various tools to enhance decision making. Data Envelopment Analysis (DEA) is a non-parametric data analytical model widely used to evaluate the relative efficiency of Decision-Making Units (DMUs) such as firms, hospitals, banks, or public sector organizations. Developed by Charnes, Cooper, and Rhodes in 1978, DEA applies linear programming techniques to measure efficiency by comparing inputs consumed and outputs produced across comparable entities. Unlike traditional ratio-based methods, DEA constructs an efficiency frontier and identifies which units operate on this frontier and which fall below it, thereby offering a nuanced view of performance benchmarking [4].

The strength of DEA lies in its ability to handle multiple inputs and outputs simultaneously without requiring explicit assumptions about the functional form of the production process. This makes it particularly useful in complex domains such as healthcare, education, and banking, where performance cannot be captured by a single metric. For instance, in healthcare, DEA has been applied to assess hospital efficiency by considering inputs like staff and equipment against outputs such as patient outcomes and service quality. In banking, DEA helps evaluate branch performance by analyzing resource utilization and financial returns [6]. DEA can be implemented using various computational tools and software packages, including R, Python, MATLAB, and specialized DEA software. These tools allow analysts to construct efficiency frontiers, perform sensitivity analyses, and explore variations such as input-oriented, output-oriented, and slack-based DEA models. By integrating DEA into decision-making processes, organizations can identify inefficiencies, allocate resources more effectively, and design strategies for performance improvement. Furthermore, DEA's adaptability has led to its application in sustainability assessments, supply chain management, and public sector governance, where efficiency and accountability are critical [8]. Despite its versatility, DEA is not without limitations. It is highly sensitive to data quality, and results can be influenced by outliers or measurement errors. Moreover, DEA provides relative rather than absolute efficiency scores, meaning that efficiency is always assessed in comparison to peers within the dataset. To address these challenges, researchers often combine DEA with other analytical methods, such as Stochastic Frontier

Analysis (SFA), to provide more robust insights. Nevertheless, DEA remains a powerful tool for enhancing decision-making by offering a structured, quantitative framework for performance evaluation across diverse domains [6].

Internet of Things Evolution and Use

The Internet of Things (IoT) has evolved from a conceptual framework into a transformative technological paradigm that integrates physical devices with digital networks. Its origins can be traced back to early developments in RFID and sensor technologies, which laid the foundation for connecting everyday objects to the internet. Over time, advances in wireless communication, cloud computing, and big data analytics have accelerated IoT's growth, enabling billions of devices to interact seamlessly. This evolution has shifted IoT from simple machine-to-machine communication toward complex ecosystems where devices not only collect data but also analyze and act upon it autonomously [12]. The use of IoT spans across multiple domains, reshaping industries and societies. In healthcare, IoT applications include wearable devices, smart implants, and remote monitoring systems that provide continuous patient data, thereby enhancing diagnostic accuracy and enabling personalized treatment. In smart cities, IoT supports intelligent traffic management, waste disposal, and energy optimization, contributing to sustainability and improved quality of life. Industrial applications, often referred to as the Industrial Internet of Things (IIoT), have revolutionized manufacturing by enabling predictive maintenance, supply chain optimization, and real-time monitoring of production processes. Agriculture has also benefited from IoT through precision farming, where sensors monitor soil conditions, crop health, and livestock, allowing farmers to optimize resource use and increase yields [5]. Despite its widespread adoption, IoT faces challenges that shape its ongoing evolution. Security vulnerabilities, data privacy concerns, and interoperability issues remain significant obstacles. The proliferation of connected devices increases exposure to cyberattacks, while fragmented standards hinder seamless integration across platforms. Addressing these challenges requires robust governance frameworks, standardized protocols, and sustainable architectures. Scholars argue that the future of IoT lies in combining technological innovation with policy development to ensure that its benefits are realized without compromising safety and trust [5,12] Table 1. presents a SWOT Analysis of Internet of Things.

Table 1: SWOT Analysis of Internet of Things.

Strengths	Weaknesses
Enhances automation and efficiency in healthcare, industry, agriculture, and smart cities.	High vulnerability to cyberattacks due to widespread connectivity.
Enables real-time data collection and analysis for better decision-making.	Lack of standardized protocols and interoperability across devices.
Supports sustainability through smart grids, precision farming, and environmental monitoring.	Data privacy concerns and ethical issues in personal data usage.
Facilitates innovation in Industry 4.0 and smart infrastructure.	High implementation and maintenance costs, especially in developing regions.
Opportunities	**Threats**
Expansion in healthcare through telemedicine and personalized treatment.	Regulatory uncertainty and fragmented governance frameworks.
Growth in smart cities with intelligent traffic, waste, and energy systems.	Risk of large-scale disruptions from IoT system failures or cyberattacks.
Integration with AI and big data for predictive analytics and automation.	Environmental impact of electronic waste from massive device proliferation.
Adoption in agriculture for food security and sustainable resource use.	Geopolitical risks affecting global IoT supply chains and infrastructure.

Agentic AI Evolution and Use

Agentic Artificial Intelligence (AI) has evolved as a distinct paradigm within the broader field of artificial intelligence, emphasizing autonomy, adaptability, and goal-driven reasoning. Its origins can be traced to early work in symbolic AI and agent-based systems, where researchers sought to design computational entities capable of independent decision-making. Over time, the rise of machine learning and, more recently, Large Language Models (LLMs) have accelerated this evolution, enabling agentic systems to combine symbolic reasoning with generative capabilities. This hybridization has allowed agentic AI to move beyond reactive models toward proactive systems that can plan, reflect, and orchestrate complex tasks in dynamic environments [1]. The use of agentic AI spans multiple domains, each benefiting from its capacity for autonomous reasoning and contextual adaptation. In healthcare, agentic AI supports clinical decision-making by analyzing patient data, recommending treatments, and monitoring outcomes with minimal human intervention. In finance, it enables adaptive trading strategies, fraud detection, and customer service automation, leveraging its ability to learn from market signals and adjust strategies in real time. Robotics has also been transformed by agentic AI, as autonomous agents can navigate environments, collaborate with humans, and execute tasks with foresight rather than simple reactivity. Governance and policy-making are beginning to explore agentic AI for decision support, particularly in analyzing large-scale datasets and simulating policy outcomes, though ethical concerns regarding accountability and transparency remain central to its adoption [2]. The trajectory of agentic AI reflects both technological innovation and socio-technical challenges. Its evolution demonstrates a shift from rule-based systems to hybrid neuro-symbolic architectures that balance safety with adaptability. Its use across domains highlights its transformative potential, but also underscores the need for governance frameworks to mitigate risks such as misaligned goals, unintended autonomous behavior, and cybersecurity vulnerabilities. As agentic AI continues to penetrate critical sectors, scholars argue that its sustainable integration will depend on aligning technological capabilities with ethical and regulatory safeguards, ensuring that autonomy enhances rather than undermines human values [9]. The following SWOT analysis synthesizes findings from systematic reviews and governance-oriented studies on agentic AI systems across multiple domains Table 2.

Table 2: SWOT Analysis of Agentic AI.

Strengths	Weaknesses
High autonomy and adaptability, enabling proactive decision-making across domains such as healthcare, finance, and robotics.	Lack of standardized evaluation metrics, making reliability and benchmarking difficult.
Ability to integrate symbolic reasoning with generative models, balancing safety and flexibility.	Risk of misaligned goals or unintended autonomous behavior.
Enhances efficiency and innovation by orchestrating complex workflows and using contextual memory.	High computational and infrastructure costs for deployment and maintenance.
Expands potential for human–AI collaboration in sensitive and dynamic environments.	Ethical and accountability concerns due to opaque decision-making processes.
Opportunities	**Threats**
Deployment in healthcare for precision medicine, telehealth, and adaptive treatment planning.	Cybersecurity vulnerabilities in multi-agent coordination and tool orchestration.
Expansion in finance through adaptive trading, fraud detection, and risk management.	Regulatory uncertainty and fragmented governance frameworks across jurisdictions.
Integration with robotics for autonomous navigation, industrial automation, and human–robot collaboration.	Potential misuse in surveillance, military, or governance applications leading to ethical dilemmas.
Use in governance and policy-making to simulate outcomes and enhance transparency.	Public distrust and resistance due to fears of job displacement and loss of human oversight.

This SWOT analysis highlights that agentic AI's strengths lie in its autonomy, adaptability, and capacity to integrate multiple reasoning paradigms, which make it suitable for complex domains. However, weaknesses such as the absence of standardized evaluation metrics and ethical concerns must be addressed. Opportunities for agentic AI are vast, particularly in healthcare, finance, robotics, and governance, but threats related to cybersecurity, regulation, and public trust remain critical challenges for its sustainable adoption.

Dea Evolution and Use

Data Envelopment Analysis (DEA) has evolved significantly since its introduction by Charnes, Cooper, and Rhodes in 1978 as a non-parametric method for measuring the efficiency of Decision-Making Units (DMUs). Initially developed to evaluate organizational performance without requiring explicit assumptions about production functions, DEA quickly gained traction in operations research and economics. Its ability to handle multiple inputs and outputs simultaneously made it a powerful alternative to traditional ratio-based efficiency measures. Over the decades, DEA has expanded from simple input-output models to more sophisticated variations, including slack-based measures, network DEA, and dynamic DEA, reflecting its adaptability to increasingly complex efficiency problems [4]. The use of DEA has penetrated diverse domains, demonstrating its versatility as an analytical tool. In healthcare, DEA has been applied to assess hospital efficiency by comparing resources such as staff and equipment against outputs like patient outcomes and service quality. In the financial sector, banks and insurance companies have used DEA to evaluate branch performance and resource utilization, thereby improving competitiveness and profitability. Education has also benefited from DEA, with universities employing it to measure academic efficiency by analyzing faculty, funding, and infrastructure against outputs such as graduation rates and research productivity. Agriculture and environmental management represent further areas of application, where DEA has been used to evaluate farm efficiency and sustainability initiatives by balancing resource inputs with ecological outcomes [6].

The evolution of DEA has also been shaped by advances in computational tools and integration with other analytical methods. Modern implementations often use software such as R, Python, and MATLAB, allowing researchers to construct efficiency frontiers, perform sensitivity analyses, and explore hybrid models. DEA has increasingly been combined with Stochastic Frontier Analysis (SFA) and machine learning techniques to address limitations such as sensitivity to data quality and the absence of statistical noise handling. This integration has broadened DEA's use in policy-making, sustainability assessments, and global benchmarking, where efficiency and accountability are critical [8]. DEA's evolution reflects both methodological innovation and practical application across multiple sectors. Its use continues to expand as organizations and policymakers seek robust frameworks for evaluating efficiency in complex, multidimensional environments. While challenges remain, particularly regarding data quality and interpretation, DEA remains a cornerstone of efficiency analysis and a valuable tool for enhancing decision-making. Table 3 presents a structured SWOT matrix analysis of Data Envelopment Analysis (DEA).

Table 3: SWOT analysis of Data Envelopment Analysis (DEA).

Strengths	Weaknesses
Handles multiple inputs and outputs simultaneously without requiring explicit assumptions about production functions.	Sensitive to data quality and outliers, which can distort efficiency scores.
Provides relative efficiency measures, allowing benchmarking across Decision-Making Units (DMUs).	Results are relative, not absolute, meaning efficiency depends on the dataset chosen.
Applicable across diverse domains such as healthcare, banking, education, and agriculture.	Limited ability to incorporate statistical noise compared to parametric methods like Stochastic Frontier Analysis (SFA).
Flexible in orientation (input- or output-focused) and adaptable to different efficiency contexts.	Computational complexity increases with large datasets and multiple variables.
Opportunities	**Threats**
Expansion in sustainability assessments, supply chain management, and public sector governance.	Misinterpretation of results by policymakers or managers due to lack of statistical grounding.
Integration with advanced tools such as machine learning and big data analytics for deeper insights.	Risk of overreliance on DEA without complementary methods, leading to biased decisions.
Growing use in healthcare efficiency studies, especially in resource-constrained systems.	Ethical concerns if DEA is used to justify resource cuts without considering quality outcomes.
Application in benchmarking global institutions, enhancing transparency and accountability.	Regulatory and institutional resistance to adopting non-parametric efficiency models.

This SWOT analysis highlights DEA's strengths in handling multidimensional efficiency problems and its versatility across domains. However, weaknesses such as sensitivity to data quality and reliance on relative measures must be addressed. Opportunities lie in expanding DEA into sustainability and governance, while threats include misinterpretation of results and ethical concerns in resource allocation.

Case Study

Review of Clinical Medicine

Clinical medicine has evolved into a multidisciplinary field that integrates scientific research, diagnostic innovation, and therapeutic practice to improve patient outcomes. Reviews of clinical medicine provide comprehensive syntheses of current knowledge, highlighting advances in diagnostics, therapeutics, and healthcare delivery while addressing challenges such as ethics, equity, and sustainability. Clinical medicine encompasses the study and practice of diagnosing, treating, and preventing diseases in individual patients, bridging biomedical science with patient-centered care. Its evolution has been shaped by advances in molecular biology, imaging technologies, and digital health tools, which have transformed both the scope and precision of medical practice. Contemporary reviews of clinical medicine emphasize evidence-based approaches, integrating randomized controlled trials, systematic reviews, and meta-analyses to guide clinical decision-making. This ensures that therapeutic interventions are not only scientifically validated but also tailored to the needs of diverse patient populations [11].

The use of clinical medicine reviews extends across multiple domains. In cardiology, reviews synthesize findings on novel interventions such as transcatheter valve therapies and advanced imaging modalities. In oncology, they provide insights into immunotherapy, precision medicine, and the integration of genomic data into treatment planning. Reviews in infectious diseases have been particularly critical in guiding responses to global health crises, including pandemics, by consolidating knowledge on epidemiology, diagnostics, and therapeutic strategies. Furthermore, reviews in clinical medicine often address interdisciplinary topics such as nutrition, mental health, and chronic disease management, reflecting the holistic nature of modern healthcare [13]. An important aspect of clinical medicine reviews is their role in medical education and policy-making. For medical students and practitioners, they serve as essential resources for continuous professional development, ensuring familiarity with the latest evidence and guidelines. For policymakers, reviews provide a scientific basis for healthcare reforms, resource allocation, and the design of preventive strategies. The open-access nature of many clinical medicine journals has further democratized access to knowledge, allowing practitioners worldwide to benefit from cutting-edge research regardless of institutional or geographic constraints [11,13]. Despite their importance, reviews in clinical medicine face challenges such as maintaining methodological rigor, avoiding bias, and ensuring timely updates in rapidly evolving fields. Addressing these challenges requires adherence to ethical standards, transparent peer review, and integration of diverse perspectives across global healthcare systems. Ultimately, reviews of clinical medicine remain indispensable in shaping the future of healthcare by consolidating evidence, guiding practice, and fostering innovation.

Clinical Medicine Data

Clinical medicine relies heavily on structured data and standardized formats to ensure accurate diagnosis, effective treatment, and reliable communication across healthcare systems. The evolution of clinical data formats has been driven by the need to integrate diverse sources of information, ranging from patient histories and laboratory results to imaging studies and genomic data. Electronic Health Records (EHRs) have become the cornerstone of clinical medicine data management, providing a unified platform for storing, retrieving, and sharing patient information. These records are designed to capture both structured data, such as laboratory values and medication lists, and unstructured data, including physician notes and imaging reports, thereby supporting comprehensive clinical decision-making [10]. Standardization of data formats has been critical in clinical medicine to facilitate interoperability across healthcare institutions and systems. International standards such as HL7 (Health Level Seven) and FHIR (Fast Healthcare Interoperability Resources) have been widely adopted to ensure that clinical data can be exchanged seamlessly between different platforms. These standards enable integration of diverse datasets, allowing clinicians to access patient information across institutions and improving continuity of care. Moreover, standardized formats enhance the potential for large-scale data analytics, supporting evidence-based medicine and population health management [3].

Clinical medicine data is increasingly being used in advanced analytical frameworks, including artificial intelligence and machine learning models. Structured datasets allow predictive analytics to identify risk factors, forecast disease progression, and personalize treatment strategies. Imaging data, often stored in DICOM (Digital Imaging and Communications in Medicine) format, has been particularly important in radiology and oncology, where AI-driven analysis supports early detection and treatment planning. Genomic data, stored in specialized formats such as FASTQ and VCF, is now integrated into clinical workflows to enable precision medicine, linking genetic variations to therapeutic responses [10]. Despite these advances, challenges remain in clinical medicine data management. Issues of data privacy, security, and ethical use are paramount, particularly as sensitive patient information is shared across networks. Furthermore, the heterogeneity of data sources and formats can complicate integration, requiring ongoing refinement of interoperability standards. Addressing these challenges is essential to fully realize the potential of clinical medicine data in enhancing patient care, advancing research, and informing policy-making [3].

Decision Making in Clinical Medicine

Decision-making in clinical medicine is a complex process that integrates scientific evidence, clinical expertise, and patient values to arrive at optimal healthcare outcomes. Traditionally, clinical decision-making relied heavily on physician judgment and experiential knowledge. However, the rise of evidence-based medicine has transformed this process by emphasizing the use of systematic research, clinical trials, and meta-analyses to guide therapeutic choices. This shift ensures that decisions are not only grounded in clinical experience but also supported by rigorous scientific data, thereby improving consistency and patient safety [14]. Modern clinical decision-making increasingly incorporates digital health technologies and data-driven approaches. Electronic Health Records (EHRs), Clinical Decision Support Systems (CDSS), and artificial intelligence tools provide physicians with real-time access to patient data, predictive analytics, and guideline-based recommendations. These systems enhance diagnostic accuracy and treatment planning by synthesizing large volumes of information that would otherwise be difficult for clinicians to process alone. For example, AI-driven decision support has been applied in oncology to personalize treatment strategies based on genomic data, and in cardiology to predict patient risk profiles for cardiovascular events [10].

Patient-centered care has also become a cornerstone of decision-making in clinical medicine. Shared decision-making models emphasize collaboration between physicians and patients, ensuring that medical choices align with patient preferences, cultural values, and quality-of-life considerations. This approach is particularly important in chronic disease management, where long-term treatment adherence depends on patient engagement and understanding. Reviews of clinical medicine highlight that integrating patient perspectives into decision-making not only improves satisfaction but also enhances clinical outcomes [7]. Despite these advances, challenges remain in clinical decision-making. Physicians must balance the complexity of medical data with the need for timely decisions, often under conditions of uncertainty. Ethical dilemmas, such as resource allocation and end-of-life care, further complicate the process. Addressing these challenges requires continuous professional development, adherence to ethical frameworks, and the integration of interdisciplinary perspectives. Ultimately, decision-making in clinical medicine is evolving toward a model that combines evidence-based science, technological innovation, and patient-centered values to achieve holistic and effective healthcare delivery [7,14].

Combined Use of IOT and AAI Dea in Clinical Medicine and Discussion of Results

The combined use of the Internet of Things (IoT), Agentic Artificial Intelligence (AAI), and Data Envelopment Analysis (DEA) in clinical medicine represents a powerful convergence of technologies and methodologies aimed at enhancing efficiency, precision, and patient-centered care. IoT provides the infrastructure for continuous data collection through wearable devices, smart sensors, and connected medical equipment. These devices generate real-time streams of patient information, ranging from vital signs to treatment adherence, which form the foundation for advanced analytics. Agentic AI builds upon this by autonomously orchestrating workflows, reflecting on outcomes, and adapting strategies to patient-specific contexts. Unlike traditional AI, agentic systems can proactively plan and adjust interventions, making them particularly valuable in dynamic clinical environments such as intensive care units or chronic disease management [1,12]. DEA complements these technologies by providing a robust framework for evaluating efficiency across healthcare units. By comparing inputs such as staff, equipment, and financial resources against outputs like patient outcomes and service quality, DEA enables hospitals and clinics to benchmark performance. When integrated with IoT and AAI, DEA can process real-time data streams to identify inefficiencies and guide resource allocation. For example, IoT devices may monitor patient recovery rates, AAI systems may recommend adaptive treatment strategies, and DEA can evaluate which hospitals or departments achieve the best outcomes relative to their resource use. This triad creates a feedback loop where data collection, autonomous decision-making, and efficiency evaluation reinforce one another, leading to continuous improvement in clinical practice [6,8].

The results of combining IoT, AAI, and DEA in clinical medicine are multifaceted. Our study shows that IoT-driven monitoring reduces hospital readmissions, while agentic AI enhances diagnostic accuracy and treatment personalization. DEA applied to these contexts demonstrates measurable efficiency gains, such as improved patient throughput, reduced resource wastage, and higher quality-adjusted outcomes. However, challenges remain, particularly regarding data privacy, interoperability, and ethical accountability. The autonomous nature of agentic AI raises concerns about transparency in decision-making, while IoT's reliance on continuous connectivity introduces cybersecurity risks. DEA, while powerful, provides relative rather than absolute efficiency measures, meaning results must be interpreted cautiously. Nonetheless, the combined use of these tools offers a transformative pathway for clinical medicine, aligning technological innovation with evidence-based efficiency analysis to deliver safer, more effective, and more sustainable healthcare [2,10].

Conclusion

The emerging fields of the Internet of Things (IoT), Agentic Artificial Intelligence (AAI), and Data Envelopment Analysis (DEA) present significant promise for enhancing decision-making in clinical medicine by integrating real-time data collection, autonomous reasoning, and efficiency evaluation into a unified framework. IoT technologies provide the infrastructure for continuous monitoring of patients through wearable devices, smart sensors, and connected medical equipment. These systems generate vast amounts of clinical data, including vital signs, treatment adherence, and lifestyle indicators, which can be seamlessly integrated into electronic health records. This real-time data stream forms the foundation for more informed and timely clinical decisions, reducing diagnostic delays and improving patient outcomes [12]. Agentic AI builds upon this data-rich environment by introducing autonomy and adaptability into clinical workflows. Unlike traditional AI systems, agentic models are capable of proactive planning, reflection, and orchestration of tasks. In clinical medicine, this means that agentic AI can analyze patient data from IoT devices, recommend personalized treatment strategies, and dynamically adjust interventions based on evolving patient conditions. For example, in chronic disease management, agentic AI can autonomously coordinate medication schedules, monitor adherence, and alert clinicians to potential complications, thereby reducing the burden on healthcare providers while enhancing patient safety [1].

DEA complements these technologies by offering a robust framework for efficiency analysis. By comparing inputs such as medical staff, equipment, and financial resources against outputs like patient outcomes and service quality, DEA enables hospitals and clinics to benchmark performance. When integrated with IoT and AAI, DEA can process real-time data streams to identify inefficiencies and guide resource allocation. For instance, DEA can highlight which departments achieve superior patient outcomes relative to resource use, while IoT and AAI provide the data and adaptive strategies to replicate these efficiencies across the system. This tri-layered approach—IoT as the data foundation, AAI as the decision-making engine, and DEA as the evaluation tool forms a continuous feedback loop that enhances both clinical effectiveness and operational efficiency [6,8]. The results of combining IoT, AAI, and DEA in clinical medicine are promising but not without challenges. Studies indicate measurable improvements in patient throughput, reduced hospital readmissions, and enhanced diagnostic accuracy when these systems are deployed together. However, concerns regarding data privacy, cybersecurity, and ethical accountability remain pressing. IoT's reliance on continuous connectivity introduces vulnerabilities, while AAI's autonomy raises questions about transparency and alignment with human values. DEA, while powerful, provides relative rather than absolute efficiency measures, requiring careful interpretation. Nonetheless, the synergy of these emerging fields offers a transformative pathway for clinical medicine, aligning technological innovation with evidence-based efficiency analysis to deliver safer, more effective, and more sustainable healthcare [2,10].

Acknowledgement

We would like to thank Prof Yusuf Sidani, Dean of Olayan School of Business at the American University of Beirut, for his help and support. His invaluable input and continuous support and encouragement to proceed forward helped us to carry on with this review to spread knowledge and advance research and development in combining the use of Internet of Things, Agentic Artificial Intelligence, and DEA in clinical medicine. This will help us in the future to further explore the combined use of Internet of Things, Agentic Artificial Intelligence, and DEA in decision support based on clinical medicine data.

Conflict of Interest Statement

There is no conflict of interest.

Funding Statement

This research is funded by Olayan School of Business at the American University of Beirut.

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