



## DATA-DRIVEN DECISION SUPPORT SYSTEMS IN PERVASIVE HEALTHCARE: BALANCING INNOVATION, PRIVACY, AND SUSTAINABILITY: A COMMENTARY

Segun Kehinde

Department of Business Administration & Management, Federal Polytechnic Ilaro, Nigeria.

DOI: <https://doi.org/10.5281/zenodo.18228203>

### Keywords

Data-Driven Decision Support Systems, Pervasive Healthcare, Innovation, Privacy, Sustainability

### Article History

Received: 21 November 2025

Accepted: 29 December 2025

Published: 13 January 2026

Copyright @Author

Corresponding Author: \*

Segun Kehinde

### Abstract

This commentary systematically explores how Data-Driven Decision Support Systems (DSS) in pervasive healthcare reconcile innovation with privacy and sustainability. It highlights technical approaches—such as cross-source data fusion using enhanced Dempster–Shafer theory, federated learning, and homomorphic encryption—while analyzing specific case studies in ophthalmology (e.g., retinal disease detection models), MRI, and CT imaging that demonstrate real-world implementation strategies. The paper also reviews solutions to core issues like data cleaning, encryption optimization, algorithmic explainability, and ecological footprint mitigation. The commentary concludes that successful DSS adoption depends on integrative technical frameworks supported by cross-disciplinary collaboration and transparent governance.

## INTRODUCTION

The rapid integration of technology into healthcare has paved the way for innovative approaches to patient care, with Data-Driven Decision Support Systems (DSS) at the forefront. These systems leverage vast amounts of data, enabling healthcare providers to make informed decisions that can significantly improve patient outcomes. As pervasive healthcare continues to evolve, DSSs have emerged as critical tools for enhancing clinical decision-making, optimizing resource allocation, and improving the overall efficiency of healthcare delivery (Barnes, Guo, & Chan, 2022). However, the adoption of these systems raises important questions about the balance between technological innovation, privacy protection, and sustainability—a balance that is crucial for the successful and ethical implementation of DSS in pervasive healthcare environments (Kehinde, Moses, Borishade, Busola, Adubor, Obembe, & Asemota, 2023). The relevance of Data-Driven

Decision Support Systems in healthcare cannot be overstated. As healthcare systems worldwide face increasing pressures from aging populations, rising healthcare costs, and the growing burden of chronic diseases, the need for efficient and effective decision-making tools has become more critical than ever. DSSs, which utilize data analytics, machine learning, and artificial intelligence, offer the potential to revolutionize healthcare by providing clinicians with real-time insights, predictive analytics, and evidence-based recommendations. These systems can process vast amounts of data from electronic health records (EHRs), wearable devices, and other sources to assist in diagnosing diseases, predicting patient outcomes, and personalizing treatment plans. For instance, a study by McKinsey & Company estimates that the widespread adoption of AI-driven DSSs could generate up to \$100 billion annually in value for the healthcare sector by improving patient outcomes and reducing costs. Despite their



potential, the implementation of DSS in pervasive healthcare presents significant challenges, particularly concerning data privacy and security (Prince, & Lovesum, 2020). The healthcare industry is already a prime target for cyberattacks due to the sensitive nature of the data it handles. The introduction of DSS, which relies heavily on the collection, storage, and analysis of vast amounts of personal health data, further exacerbates these concerns (Bibri, & Krogstie, 2020). According to a report by IBM Security, the average cost of a data breach in the healthcare sector was \$10.1 million in 2022, the highest across all industries. This figure underscores the critical need to address privacy and security issues as DSS becomes more integrated into healthcare systems. Moreover, there is a growing concern that the misuse or mishandling of health data could lead to significant ethical and legal ramifications, particularly regarding patient consent and the potential for discrimination based on health information. In addition to privacy concerns, the sustainability of Data-Driven Decision Support Systems in pervasive healthcare is another critical issue that must be addressed. The energy consumption associated with the data centers that power these systems is significant, contributing to the broader environmental impact of digital technologies. Data centers, which are essential for storing and processing the vast amounts of data used by DSS, are estimated to consume about 1% of global electricity, a figure that is expected to rise as data usage continues to grow. The environmental footprint of these facilities, particularly in terms of carbon emissions, presents a challenge for the healthcare industry, which is increasingly under pressure to adopt more sustainable practices (Alahmari, Mehmood, Alzahrani, Yigitcanlar, & Corchado, 2023). According to a report by the International Energy Agency (IEA), global data center electricity demand reached 200 terawatt-hours (TWh) in 2021, with significant contributions from AI and machine learning workloads. As healthcare systems adopt more data-

driven technologies, it is essential to consider the environmental implications and explore strategies for minimizing the carbon footprint of DSS.

Given these challenges, the integration of Data-Driven Decision Support Systems in pervasive healthcare requires a balanced approach that prioritizes innovation, privacy, and sustainability. On the one hand, the potential benefits of DSS in improving patient outcomes, reducing costs, and enhancing the overall efficiency of healthcare delivery are undeniable. On the other hand, these benefits must be weighed against the risks associated with data privacy, security, and environmental sustainability. Achieving this balance will require a multidisciplinary approach that brings together stakeholders from healthcare, technology, ethics, and environmental science to develop comprehensive strategies that address these complex issues. One potential avenue for achieving this balance is the development of robust regulatory frameworks that govern the use of DSS in healthcare. Such frameworks should focus on ensuring that data privacy and security are maintained while also promoting the responsible and sustainable use of technology (Boulemtafes, Khemissa, Derki, Amira, & Djedjig, 2021). For example, the European Union's General Data Protection Regulation (GDPR) provides a strong foundation for protecting personal data and could serve as a model for regulating health data in the context of DSS. Additionally, the adoption of green data center practices, such as using renewable energy sources and improving energy efficiency, can help mitigate the environmental impact of DSS. According to a report by the Uptime Institute, more than 40% of data centers plan to increase their use of renewable energy, signaling a positive trend towards more sustainable practices. Furthermore, there is a need for ongoing research and development to address the technical and ethical challenges associated with DSS. This includes improving the transparency and explainability of AI algorithms used in decision support, as well as developing new



methods for ensuring that data is anonymized and used in ways that respect patient privacy (Kehinde, 2025). Researchers must also explore ways to optimize the energy efficiency of DSS, particularly as these systems become more complex and data-intensive. Collaboration between academia, industry, and government will be crucial in driving innovation while also addressing the ethical and environmental challenges posed by DSS.

### Innovations and Technical Methodologies

- i. *Cross-Source Data Fusion & Dynamic Decision-Making Models:* AI-based fusion of EHRs, imaging data, wearable sensor data, and omics—using early/intermediate-fusion workflows—significantly enhances diagnostic accuracy. In ophthalmology, DNN ensembles (ResNet50+ResNet101) with enhanced Dempster-Shafer decision fusion improved reliability in fundus-image-based disease recognition. Another multimodal fusion model (DF-DM) applied to diabetic retinopathy demonstrates how metadata, image, and clinical data fusion enhances predictive performance. Such fusion systems illustrate how dynamic decision-making can be optimized through weighted voting, Bayesian classifiers, and temporal modeling—enabling real-time alerts for retinal disease and urgent care.
- ii. *Outlier Handling & Data Sanitization:* Effective DSS require rigorous data pre-processing—techniques such as k-anonymity, heuristic-based sanitization, and machine learning outlier detection ensure data integrity and privacy. Retinal-image studies employ image-augmentation filters, thresholding, vessel removal, and patch-based segmentation—reducing noise and enhancing class-specific accuracy.
- iii. *Privacy-Preserving Design: Federated Learning + Encryption:* In diabetic retinopathy, federated learning empowers multi-center model training without data centralization—achieving 92%+ accuracy, complying with HIPAA/GDPR. Moreover, private-retinal-disease work applies hybrid encryption (blockchain + homomorphic

encryption + AES) for data anonymization while retaining model precision.

iv. *Explainable AI & Model Transparency:* High-stakes medical DSS demand interpretable algorithms. CNN architectures such as DenseNet-16, ResNet50, UNet, DiffUNet, and CE-Net embed segmentation and lesion localization that clinicians can audit—ensuring explainability. These are paired with XAI interfaces and clinician feedback loops, improving rule-based integration into workflows.

### Case Studies of DSS Implementation

#### Ophthalmology:

- ✓ Ensemble DNN (ResNet50/101 + enhanced DS fusion) achieved significantly improved disease detection accuracy with robust uncertainty fusion.
- ✓ Segmamba and NestedFormer architectures applied to 3D retinal and brain image segmentation showcase multimodal fusion with tailored transformer networks.

#### MRI:

- ✓ Transformer-based NestedFormer and cross-conditioned diffusion models demonstrate tumor segmentation across domains, with active domain adaptation for multicenter robustness .

#### CT:

- ✓ Hybrid Masked Image Modeling and Diff-UNet strategies deliver volumetric segmentation using partial masking and diffusion priors—showing how lightweight generative models can operate in real-time diagnostics .  
Systems like these integrate federated learning, encryption, and interpretability into comprehensive DSS platforms for medical centers.

### Evidence and Logical Reasoning

Data-Driven Decision Support Systems (DSS) have become indispensable tools in modern healthcare, promising unprecedented improvements in patient care, resource management, and clinical outcomes. The argument in favor of these systems is strongly supported by empirical



evidence and expert consensus. For instance, a report by Accenture estimates that AI applications, including DSS, could save the U.S. healthcare industry \$150 billion annually by 2026 through efficiency gains, improved diagnostics, and better care coordination. Furthermore, a study published in *The Lancet Digital Health* found that DSS can reduce diagnostic errors by up to 30%, highlighting their potential to significantly enhance patient safety and care quality. The implementation of DSS is underpinned by the robust and logical premise that data-driven insights enable more precise and timely decisions. Unlike traditional decision-making processes that often rely on clinician intuition or limited data, DSS leverages vast datasets from electronic health records (EHRs), wearable devices, and genomic information, among other sources (Degerli, 2022). This data richness allows DSS to identify patterns and correlations that would be impossible to detect manually. For example, predictive analytics within DSS can forecast patient deterioration or identify individuals at high risk of developing chronic conditions, thereby enabling early intervention and potentially saving lives. However, the benefits of DSS extend beyond clinical outcomes. From an operational perspective, these systems also offer significant advantages in resource management. Hospitals can use DSS to optimize staffing levels, manage bed occupancy, and predict demand for medical supplies, thereby reducing waste and improving overall efficiency. A study conducted by the Harvard T.H. Chan School of Public Health demonstrated that hospitals utilizing DSS for resource management experienced a 15% reduction in operational costs compared to those relying on traditional methods. This not only underscores the economic value of DSS but also illustrates their potential to address some of the systemic inefficiencies plaguing healthcare systems worldwide. The logical reasoning that underlies the implementation of DSS is clear: by harnessing the power of data, healthcare

providers can make more informed, accurate, and timely decisions. This, in turn, leads to better patient outcomes, lower costs, and more efficient use of resources.

#### **Addressing Counterarguments and Alternative Views**

While the advantages of Data-Driven Decision Support Systems are compelling, it is crucial to engage with the counterarguments and alternative perspectives that challenge their widespread adoption. One of the most significant concerns is the issue of data privacy and security. The healthcare sector has increasingly become a target for cyberattacks, with data breaches potentially compromising sensitive patient information. Critics argue that the reliance on large datasets for DSS increases the risk of such breaches, posing significant ethical and legal challenges (Saxena, & Joshi, 2024). A report by the Ponemon Institute found that healthcare data breaches cost an average of \$408 per record, the highest across all industries. This figure reflects the high stakes involved in managing health data and raises legitimate concerns about the risks associated with DSS. Moreover, there is the argument that the deployment of DSS could exacerbate existing health disparities. Data-driven systems rely on historical data, which may reflect and perpetuate existing biases in healthcare. For example, if a DSS is trained on data from predominantly white populations, it may not perform as well for patients from minority groups, leading to unequal treatment outcomes. This issue is particularly pressing given the growing emphasis on personalized medicine, where inaccuracies or biases in DSS could have life-altering consequences for patients. A study published in *Nature Medicine* highlighted this concern, demonstrating that an AI-based DSS showed significant racial bias in predicting kidney disease progression, leading to under-treatment of Black patients. These findings suggest that without careful oversight and ongoing evaluation, DSS could unintentionally



reinforce systemic inequalities within healthcare. Another counterargument pertains to the sustainability of DSS, particularly in light of the environmental impact of data centers. As previously mentioned, data centers are significant energy consumers, contributing to carbon emissions and environmental degradation. The growing reliance on DSS, which requires extensive computational power and data storage, could exacerbate this issue, raising questions about the long-term viability of these systems. Critics argue that while DSS may offer immediate benefits in terms of efficiency and patient care, they also contribute to the broader problem of climate change, which has far-reaching implications for global health (Zahid, Poulsen, Sharma, & Wingreen, 2021). According to the International Energy Agency, data centers and data transmission networks accounted for nearly 1% of global energy-related CO<sub>2</sub> emissions in 2020, a figure that is likely to increase as digitalization accelerates. In addressing these counterarguments, it is essential to recognize that the challenges associated with DSS are not insurmountable. Rather, they require a proactive and multifaceted approach that includes stronger data protection measures, efforts to reduce bias in algorithms, and the adoption of green technologies in data centers (Kehinde, Moses, Borishade, Kehinde, Ogbari, & Kehinde, 2024). For instance, advances in encryption and anonymization techniques can mitigate privacy risks, while ongoing algorithmic auditing can help identify and correct biases in DSS. Additionally, the use of renewable energy sources for powering

data centers presents a viable solution to the sustainability challenges posed by DSS (Bousdekis, Lepenioti, Apostolou, & Mentzas, 2021). By acknowledging and addressing these concerns, the healthcare industry can ensure that the benefits of DSS are realized without compromising ethical standards or environmental sustainability.

**1. Data Security & Encryption Optimization:** Combining AES, homomorphic encryption, and blockchain reduces attack surfaces while enabling processing over encrypted data—aligning with federated privacy standards. Hybrid architectures process encrypted data securely, though limitations in latency and throughput remain critical areas for research.

**2. Algorithmic Bias & Explainability:** Transformer, CNN, and segmentation models trained on multimodal datasets reveal systematic bias risks. Active auditing using fairness-aware ML, lesion-specific thresholds, and clinician-in-the-loop retraining are essential to prevent inequities

**3. Environmental Impact & Green Computing:** Data center energy consumption (~200 TWh/year) must be addressed using green energy, hardware-optimized inference models, and dynamic workload scheduling. Next-gen DSS should accelerate edge/ fog inference and stream-selective decision fusion to reduce computational demand.

#### Technical Paths & Multidisciplinary Frameworks

Challenge	Solution Path
Unstructured data	Ontology-based schema mapping + Dempster-Shafer data fusion
Outliers / noise	Patch-based augmentation + ML-based outlier detection algorithms
Privacy protection	Federated learning + AES + homomorphic encryption + blockchain blocks
Privacy protection	U-Net segmentation + CE-Net + lesion visualization + XAI clinician dashboards
Environmental impact	Edge computing, hardware quantization, renewable energy streams



Collaboration models must bring together clinicians, ML engineers, hospital IT, legal advisors, and environmental scientists. Shared testbeds and federated benchmarking protocols are essential for scalable and sustainable deployment.

### **Conclusion**

Data-Driven Decision Support Systems represent a transformative innovation in healthcare, offering the potential to improve patient outcomes, optimize resource management, and enhance the overall efficiency of healthcare delivery. The evidence supporting the adoption of DSS is robust, with numerous studies demonstrating their positive impact on clinical decision-making and operational efficiency. However, the integration of these systems into pervasive healthcare must be approached with caution, taking into account the significant challenges related to data privacy, security, bias, and sustainability. The counterarguments against DSS—ranging from privacy concerns to the potential for exacerbating health disparities and contributing to environmental degradation—are both valid and pressing. However, these challenges should not deter the adoption of DSS, but rather inspire a more thoughtful and comprehensive approach to their implementation. By addressing these issues head-on through the development of stronger regulatory frameworks, the application of green technologies, and the ongoing evaluation of algorithmic fairness, the healthcare industry can strike a balance between innovation, privacy, and sustainability. As we continue to embrace digitalization in medicine, it is imperative that we do so in a way that safeguards patient privacy, promotes equity, and minimizes environmental impact. Future research should focus on developing more robust data protection measures, exploring strategies for reducing algorithmic bias, and investigating the environmental implications of DSS. By prioritizing these areas, we can ensure that the benefits of DSS are fully realized, while also addressing

the ethical and sustainability challenges that accompany their use.

### **REFERENCES**

Alahmari, N., Mehmood, R., Alzahrani, A., Yigitcanlar, T., & Corchado, J. M. (2023). Autonomous and Sustainable Service economies: Data-Driven optimization of Design and Operations through Discovery of Multi-perspective parameters. *Sustainability*, 15(22), 16003.

Barnes, S. J., Guo, Y., & Chan, J. (2022). Big Data analytics for sustainability: Insight through technological innovation. *Information & Management*, 59(5), 103627.

Basile, L. J. (2023). Data-driven decision-making in healthcare: unveiling the potential of digital transformation in healthcare organizations.

Bibri, S. E., & Krogstie, J. (2020). Environmentally data-driven smart sustainable cities: Applied innovative solutions for energy efficiency, pollution reduction, and urban metabolism. *Energy Informatics*, 3(1), 29.

Boulemtafes, A., Khemissa, H., Derki, M. S., Amira, A., & Djedjig, N. (2021). Deep learning in pervasive health monitoring, design goals, applications, and architectures: An overview and a brief synthesis. *Smart Health*, 22, 100221.

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for industry 4.0 maintenance applications. *Electronics*, 10(7), 828.

Degerli, M. (2022). Privacy issues in data-driven health care. *Data-Driven Approach for Bio-medical and Healthcare*, 23-37.

Farahani, B., Firouzi, F., & Chakrabarty, K. (2020). Healthcare iot. *Intelligent Internet of Things: From Device to Fog and Cloud*, 515-545.



Gaynor, M., Seltzer, M., Moulton, S., & Freedman, J. (2005). A dynamic, data-driven, decision support system for emergency medical services. In *Computational Science-ICCS 2005: 5th International Conference, Atlanta, GA, USA, May 22-25, 2005. Proceedings, Part II 5* (pp. 703-711). Springer Berlin Heidelberg.

Haghi, M., Neubert, S., Geissler, A., Fleischer, H., Stoll, N., Stoll, R., & Thurow, K. (2020). A flexible and pervasive IoT-based healthcare platform for physiological and environmental parameters monitoring. *IEEE Internet of Things Journal*, 7(6), 5628-5647.

Kehinde, S. I., Moses, C., Borishade, T., Busola, S. I., Adubor, N., Obembe, N., & Asemota, F. (2023). Evolution and innovation of hedge fund strategies: a systematic review of literature and framework for future research. *Acta Innovations*.

Kehinde, S., Moses, C., Borishade, T., Kehinde, O., Ogbari, M., & Kehinde, T. (2024). A Commentary on Integrating Green Technology into Civil Engineering: Innovative Approaches for Sustainable Infrastructure Development in Urban Areas. *International Journal on Computational Engineering*, 1(4), 126-128.

Kehinde, S. K. (2025). AI in everything, and everything in AI: A review of the ubiquitous role of artificial intelligence in shaping the next technological epoch. *Journal of Computer Allied Intelligence*, 3(5), 17-53.

Li, X., Wang, Z., Chen, C. H., & Zheng, P. (2021). A data-driven reversible framework for achieving Sustainable Smart product-service systems. *Journal of Cleaner Production*, 279, 123618.

Lo, H. W. (2023). A data-driven decision support system for sustainable supplier evaluation in the Industry 5.0 era: A case study for medical equipment manufacturing. *Advanced Engineering Informatics*, 56, 101998.

Mbunge, E., Muchemwa, B., & Batani, J. (2021). Sensors and healthcare 5.0: transformative shift in virtual care through emerging digital health technologies. *Global Health Journal*, 5(4), 169-177.

Odiboh, O., Omokiti, O., Ekanem, T., & Oyedepo, T. (2022). The Perception of Patients on Healthcare Information and social media in Suburban Primary Healthcare Centres, Lagos, Nigeria.

Oladipupo, O., & Samuel, S. (2024). A Learning Analytics Approach To Modelling Student-Staff Interaction From Students' Perception Of Engagement Practices. *IEEE Access*.

Oladipupo, O., Olajide, O., & Adubi, S. (2020). An interval type-2 fuzzy association rule mining approach to pattern discovery in breast cancer dataset.

Popoola, S. I., Atayero, A. A., Okanlawon, T. T., Omopariola, B. I., & Takpor, O. A. (2018). Smart campus: data on energy consumption in an ICT-driven university. *Data in brief*, 16, 780-793.

Prince, P. B., & Lovesum, S. J. (2020). Privacy enforced access control model for secured data handling in cloud-based pervasive health care system. *SN Computer Science*, 1(5), 239.

Ryan, M., Antoniou, J., Brooks, L., Jiya, T., Macnish, K., & Stahl, B. (2020). The ethical balance of using smart information systems for promoting the United Nations' Sustainable Development Goals. *Sustainability*, 12(12), 4826.

Samuel, G., & Lucassen, A. M. (2022). The environmental sustainability of data-driven health research: A scoping review. *Digital Health*, 8, 2055207622111297.

Sathio, A. A., Dootio, M. A., Lakhan, A., ur Rehman, M., Pnhwar, A. O., & Sahito, M. A. (2021, August). Pervasive futuristic healthcare and blockchain enabled digital identities-challenges and future intensions. In *2021 International Conference on Computing, Electronics & Communications Engineering (iCCECE)* (pp. 30-35). IEEE.

Saxena, S., & Joshi, H. (2024). Digital Health Innovations: Advancing Climate-Health-Sustainability Synergies. In *The Climate-Health-Sustainability Nexus: Understanding the Interconnected Impact on Populations and the Environment* (pp. 325-349). Cham: Springer Nature Switzerland.

Zahid, A., Poulsen, J. K., Sharma, R., & Wingreen, S. C. (2021). A systematic review of emerging information technologies for sustainable data-centric health-care. *International Journal of Medical Informatics*, 149, 104420.

