

AI Wearable Devices as a Case Study for Research on the Health Big Data Economy

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Abstract. Against the backdrop of a growing global burden of chronic diseases and the deepening digital transformation, AI wearable devices-serving as crucial gateways for health data collection and intelligent analysis-are reshaping the operational logic and value-creation pathways of the health economy. This paper systematically explores the economic mechanisms and practical impacts of AI wearable devices throughout the processes of health big data collection, processing, and application. The research findings indicate that AI wearables have evolved from simple fitness-tracking tools into comprehensive “health managers” equipped with functions such as disease warning and remote monitoring. The vast, high-frequency, and multidimensional health data generated by these devices, when processed through algorithmic modeling and delivered as services, have significantly reduced individual healthcare expenditures, optimized the allocation of medical resources, and fostered emerging industries such as Insurtech and telemedicine. However, their development also faces tangible challenges, including risks of data privacy breaches, widening health inequality, a lack of data standardization, and lagging regulatory frameworks. By constructing a “technology-data-economy” transmission chain, this study reveals the role and constraints of AI wearable devices within the economic system, offering both theoretical and empirical insights into understanding the economic transformation driven by health big data.

Keywords: AI wearable devices, health big data, economic mechanism, data privacy, policy governance.

1. Introduction

With the intensification of global population aging and changes in lifestyle, health issues have become increasingly severe. According to the World Health Organization (WHO) Report 2023, approximately 420 million adults worldwide suffer from diabetes, accounting for 8.3% of the global adult population [1]. The high prevalence of diabetes and cardiovascular diseases not only undermines patients’ quality of life but also places a heavy burden on global health systems. The traditional “treatment-oriented” medical model can no longer meet the growing needs of aging populations [2]. This is particularly true in low- and middle-income countries, where healthcare resources remain concentrated in emergency and curative care, with insufficient investment in prevention and early diagnosis.

To address these challenges, a global digital transformation in health care is underway. Digital health is not merely an emergency response mechanism but an inevitable trend aligned with the upgrading of health needs. Through early warning and intervention, digital tools can effectively reduce disease incidence and mortality rates, as well as lower treatment costs. The widespread use of intelligent health devices has provided crucial support for this transformation. These devices continuously collect and analyze health data in real time, integrating artificial intelligence (AI) and big data technologies to enhance precision and personalization in health management, thereby driving the transformation of the health economy.

As digital technologies advance, health management is gradually shifting toward proactive, precise, and individualized approaches. The traditional model of reactive treatment is no longer the sole option; greater resources are now being directed toward disease prevention, early detection, and lifestyle management. This transformation not only elevates global health outcomes but also accelerates the intelligent upgrading of the health big data and medical industries.

Health big data exhibits significant scale effects and positive externalities, characteristics that make it an increasingly vital component of global health management systems. As data volumes expand, the accuracy of health information and the predictive capacity for diseases have improved dramatically. Specifically, with the accumulation of user data, AI algorithms can more precisely identify health risk patterns and detect potential disease threats in advance, thereby enabling more personalized health interventions [3, 4]. Such interventions not only reduce the probability of major illnesses at the individual level but also lower medical expenditures arising from disease treatment, effectively alleviating the overall healthcare cost burden.

For governments, the integration and analytical capabilities of health big data provide powerful tools for public health decision-making and the efficient allocation of medical resources. By analyzing vast health datasets, policymakers can detect early signals of epidemic outbreaks and take timely measures—such as vaccine distribution and quarantine implementation—to minimize disease transmission and socioeconomic losses. Moreover, the extensive application of health data supports the formulation and evaluation of public health policies, making public health governance more refined and evidence-based.

2. Theoretical Framework and Research Perspectives

2.1. The Economic Logic of Health Big Data: Scale Effects, Externalities, and Privacy

As discussed above, one of the core features of health big data lies in its remarkable scale effects and positive externalities. In essence, data generated by individuals can be analyzed and utilized repeatedly, achieving high efficiency in data use and maximizing its value. However, the extensive application of health big data has also raised complex issues concerning data ownership and privacy protection. Although users are the producers of health data, corporations typically control its storage and analysis, leading to an asymmetric distribution of data rights. Most users lack adequate awareness and control over how their health data are used; companies often fail to fully disclose the specific purposes and potential risks associated with data collection, storage, and analysis. Furthermore, anonymization alone cannot entirely eliminate the risk of privacy breaches—especially when combined with other datasets, which may allow for re-identification of individuals.

From an economic perspective, the externalities inherent in health big data can lead to market failures. Due to the asymmetry between data users and beneficiaries, firms may prioritize profit maximization while neglecting user privacy and social responsibility. Thus, a key challenge lies in striking a balance between promoting the use of health big data and safeguarding individual privacy.

To address this issue, scholars have proposed multiple approaches, including enhancing transparency in data usage, improving informed consent mechanisms, and establishing user data control rights. These institutional measures aim to mitigate privacy risks within health big data applications and promote its sustainable and ethical development in the field of public health.

2.2. The Framework of Technological Diffusion and Innovation Economics

The diffusion process of AI wearable devices can be understood through Everett Rogers' Diffusion of Innovations Theory [2]. According to Rogers, technology adoption follows a predictable pattern comprising five groups: innovators, early adopters, early majority, late majority, and laggards. The adoption of AI wearable devices has followed a similar trajectory. Initially, these devices were embraced by a small group of technology enthusiasts and health-conscious individuals. As the technology matured and costs declined, the devices gradually gained acceptance among broader user groups.

The integration of AI algorithms has further amplified the economic value of technological innovation, forming a “hardware gateway + algorithm empowerment” model [5]. By analyzing users' health data, AI algorithms enable personalized health management and prediction. From an economic standpoint, the diffusion of AI wearable devices aligns with the principles of economies of scale and network effects. As the number of users increases, production costs decrease, lowering unit costs;

simultaneously, larger datasets provide richer training samples for AI algorithms, enhancing their accuracy and practical utility.

3. Intelligent Wearable Devices and Health Big Data

3.1. Functions and Data Collection Mechanisms of Wearable Devices: From “Basic Monitoring” to “Disease Prediction”

Mainstream intelligent wearable devices have undergone three major stages of functional evolution, reflecting both technological advancement and shifting market demand.

The first stage, prior to 2020, can be characterized as the basic monitoring phase. During this period, wearable devices primarily focused on basic fitness tracking functions such as step counting, distance measurement, and calorie expenditure. These devices utilized photoplethysmography (PPG) technology for heart rate monitoring, allowing users to record daily activity levels [5, 6]. Their medical functionality was limited, serving mainly to satisfy users’ basic health monitoring needs.

The second stage, spanning 2020 to 2022, marked the vital signs expansion phase. With improvements in sensor technology, wearables began to incorporate more advanced health monitoring functions covering a broader range of physiological indicators. For instance, the Apple Watch Series 10 introduced an electrical heart sensor enabling electrocardiogram (ECG) functions capable of detecting irregular cardiac rhythms [3, 4]. It also integrated blood oxygen, temperature, and depth sensors, offering continuous heart rate monitoring, sleep quality analysis, and exercise intensity tracking. These developments substantially enhanced the devices’ health management capabilities.

The third stage, emerging between 2023 and 2024, is characterized as the disease prediction and medical integration phase. The convergence of AI algorithms and multi-sensor systems has propelled wearable devices toward medical-grade applications. Devices now not only monitor health indicators but also predict potential health issues and provide early warnings. For example, the Fitbit Sense 2 features a “respiratory rate monitoring” function that, when combined with AI modeling, can predict pneumonia risk. In blood glucose and blood pressure monitoring, the Samsung Galaxy Watch 6 and Huawei Watch 4 Pro have achieved accurate continuous monitoring through optical sensors and micro-pump pressurization technologies, respectively [2, 5].

As these functionalities expand, the interconnection between wearable devices and healthcare systems continues to strengthen. The technological evolution and market transformation behind this trend underscore the growing potential of the health big data economy.

3.2. The Role of Artificial Intelligence in Data Processing: From “Storage” to “Prediction”

In the realm of health data processing, AI technology—particularly deep learning models—can extract latent patterns from complex health datasets, enabling early risk detection and personalized interventions. For instance, the Huawei Watch GT2 series applies heart rate variability algorithms combined with users’ sleep quality data to automatically adjust the duration of the “Do Not Disturb” mode at night and to recommend meditation exercises to improve sleep quality [7].

AI’s role in health data processing extends beyond disease prediction and individualized interventions. It also contributes to optimizing healthcare resource allocation and refining public health management strategies. As technological progress deepens and application scenarios broaden, AI is expected to play an increasingly pivotal role within the health big data economy, driving both efficiency and innovation.

3.3. The Value Chain of Health Big Data: A Closed Loop from Collection to Application

The value chain of health big data encompasses the entire process—from data collection to application—forming a closed-loop system. The specific flow includes data collection (via wearable devices) → data storage (on cloud-based platforms) → data analysis (through AI algorithmic platforms) → data application.

A notable example is the American Insurtech company Oscar Health, which integrates wearable device data into its insurance pricing model. The company provides members with free Misfit Flash fitness trackers and uses its mobile application to monitor users' daily step counts, exercise frequency, and other behavioral health data.

Overall, this closed-loop system of health big data enables increasingly refined and personalized health management, demonstrating how data-driven innovation is reshaping both the healthcare and insurance industries.

4. Analysis of the Economic Effects of Health Big Data

4.1. Micro-Level: Individual Health Optimization and Enterprise Service Upgrading

Health big data has significantly reduced individual medical expenditures and stimulated service innovation among enterprises. For example, a Stanford University study found that users of smartwatches capable of monitoring heart rate and blood oxygen levels experienced a 34% reduction in emergency visits caused by palpitations or hypoxemia, resulting in an average annual healthcare cost reduction of approximately USD 200 [8,9]. This demonstrates that intelligent wearable devices play a vital role in identifying health risks at an early stage and reducing emergency medical demand.

In the enterprise sector, insurance companies and healthcare providers are leveraging health data to develop innovative services. Oscar Health, for instance, analyzes users' wearable data—such as step count and exercise frequency—to offer 15–20% premium discounts to policyholders who maintain healthy lifestyles. Similarly, Philips has developed a remote chronic disease management platform based on wearable data, which improves blood glucose control among diabetic patients [10, 11]. These applications not only enhance the efficiency of individual health management but also drive the upgrading of services in the insurance and healthcare industries.

4.2. Macro-Level: Healthcare Resource Allocation and Public Health Decision-Making

At the macro level, health big data has optimized healthcare resource allocation and improved the overall efficiency of medical systems. The United Kingdom's National Health Service (NHS), for example, has integrated wearable device data with electronic medical records, extending follow-up intervals for hypertensive patients from three months to six months—saving approximately £120 million in medical expenditures [12]. Additionally, health big data has strengthened disease surveillance capabilities. The U.S. Centers for Disease Control and Prevention (CDC) use wearable device data to identify abnormal increases in influenza-like illness cases two weeks in advance, providing crucial support for vaccine distribution strategies [13].

The rapid growth of the global health technology industry also illustrates the economic potential of health big data. The global health tech market expanded from USD 150 billion in 2020 to USD 280 billion in 2023, with AI wearable devices and related services accounting for over 40% of the total. This trend highlights health big data as an emerging driver of global GDP growth.

5. Challenges and Risks: Key Constraints on the Value Realization of Health Big Data

AI wearable devices exhibit enormous economic potential in the health big data sector. However, their sustainable development faces multiple challenges and risks, not only stemming from technological limitations but also from institutional frictions and issues of social equity in the process of data marketization.

5.1. Data Privacy and Security: The “Sword of Damocles” Hanging Over Public Trust

5.1.1. Direct economic losses and trust erosion from personal data breaches

As smart wearable devices expand their data collection from basic activity monitoring to more sensitive health information—such as heart rate variability, atrial fibrillation risk, and blood glucose trends—the value and sensitivity of such data have risen sharply. Surveys show that 71% of users express concern about data misuse, fearing that insurers may raise premiums based on health analytics, employers may use data to influence promotion decisions, or hackers may steal private information [14]. Data breaches cause not only direct economic losses (e.g., medical fraud, insurance denial) but also undermine public trust. Users may abandon devices due to privacy concerns, weakening the scale effects of health data and reducing the accuracy of predictive models. Studies indicate that if 20% of users discontinue device use over privacy worries, the accuracy of related health warning systems could drop by 15–20% [15].

5.1.2. Ambiguities in data ownership and deep-seated ethical conflicts

The issue of health data ownership remains highly contentious. Users often view themselves as data creators who should retain full control, while device manufacturers argue that their substantial R&D investments justify data monetization. Medical institutions, meanwhile, seek access to anonymized data to support clinical research. This multi-stakeholder tension results in ambiguous ownership structures. For example, the ECG data collected by Apple Watch contain both personal health information and aggregated datasets that can form public risk models, blurring the boundary between private and public data.

In 2024, a U.S. health technology company faced a lawsuit for failing to inform users of their high future risk of diabetes [12]. The court ruled that companies must proactively notify users once predictive results reach a clinically significant intervention threshold. Moreover, data protection for vulnerable groups—such as children and the elderly—remains a particularly sensitive issue. Disputes persist between parents and manufacturers over the use of data from children’s smartwatches, reflecting the ongoing challenge of balancing data utilization with privacy protection.

5.2. Health Inequality: Widening “Digital Divide” and the Intensification of Health Stratification

5.2.1. “Income–age–education” stratification in device penetration

The global diffusion of wearable devices displays pronounced inequality. According to Statista (2024), penetration rates exceed 60% in high-income countries (e.g., the U.S., Germany, Japan) but remain below 10% in low-income countries (e.g., India, Nigeria, Bangladesh). Among those aged 65 and older, adoption rates are only one-third that of individuals aged 18–35. Furthermore, ownership among individuals with a high school education or below is 42% lower than among those with a bachelor’s degree or higher [16].

This stratification leads directly to representational bias in health data. For example, the “normal blood pressure range” detected by wearables is modeled primarily on data from middle- and high-income adults, while elderly populations in low-income communities—who often experience higher salt intake and limited access to healthcare—are underrepresented (with device usage rates as low as 8%) [15]. Consequently, disease prediction models trained on skewed datasets exhibit higher error rates, with clinical tests showing 12% higher rates of missed diagnoses for these groups.

5.2.2. Social gaps in health data utilization and the “matthew effect”

Even when low-income individuals own wearable devices, their ability to translate data into economic or health benefits is much weaker than that of higher-income users. Collaborations between technology companies and insurers are often targeted toward premium clients. Low-income users, even with basic devices, are frequently excluded from such partnerships and cannot access equivalent benefits.

The problem of digital exclusion is even more pronounced among older adults. Many elderly users are unable to upload or interpret their data through apps, meaning their health conditions remain invisible to healthcare systems. Consequently, groups with weak data utilization capacity—such as low-income seniors—face higher risks of chronic disease deterioration, escalating medical costs, and reduced work capacity, which further deepen economic hardship. Conversely, groups with strong data literacy—typically younger and wealthier individuals—maintain better health through precise interventions, forming a “health–wealth” positive feedback loop. This Matthew Effect extends health inequality beyond outcome disparities to systemic inequities in the data-driven process itself.

5.3. Technological and Institutional Bottlenecks: The Dual Constraints of Standardization Gaps and Regulatory Lag

5.3.1. Fragmentation barriers in data standardization

Global wearable technology lacks unified technical standards, resulting in significant discrepancies across brands in data formats, measurement accuracy, and analytical logic. For instance, Apple Watch employs dynamic calibration algorithms, Huawei Watch utilizes multi-sensor fusion, and Samsung Galaxy Watch relies on infrared compensation technology. Such inconsistencies hinder cross-brand data integration. According to the IDC 2023 Technical Comparison Report, multinational research projects integrating data from multiple brands often incur additional costs and delays due to format incompatibility and algorithmic variance.

5.3.2. Regulatory lag and the risk of a “legal vacuum”

Most countries still define health data within the framework of traditional medical records (e.g., clinical notes, laboratory reports) and lack specific regulations addressing “health data generated by wearable devices.” This regulatory lag creates legal uncertainty for multinational corporations in areas such as data storage and cross-border sharing.

In 2024, a data sovereignty dispute arose between the European Union and the United States involving Apple Inc. Apple stored European users’ health data in an Irish data center, while U.S. law enforcement requested access to portions of the data (including users’ activity trajectories and abnormal heart rate records) under the pretext of anti-terrorism investigations. The EU, citing the General Data Protection Regulation (GDPR), denied the request, while the U.S. invoked “data sovereignty” concerns. The eventual compromise required Apple to establish localized servers for European users—raising operational costs by 25%—but also highlighting the growing compliance risks faced by multinational health technology firms [12].

6. Policy Recommendations

6.1. Establishing a data governance framework

To ensure the effective utilization of health big data, it is essential first to clarify the ownership of health data. A “user authorization + hierarchical usage” model is recommended, under which users retain full ownership of their health data and may grant specific entities permission to use the data within defined scopes. Additionally, the development of globally unified data standards is crucial to facilitate interoperability, enhance data quality, and support international research collaboration.

6.2. Promoting industrial innovation and institutional synergy

Governments should employ policy instruments such as tax incentives and public procurement to stimulate technological innovation. For example, income tax reductions for start-ups developing health-related algorithms can lower R&D costs and foster technological advancement. At the same time, regulators should encourage innovation in the “insurance + data” model, allowing insurance companies to design differentiated products based on compliant health data usage. This policy synergy between industry and regulation can accelerate the transformation of the digital health sector and promote sustainable growth.

6.3. International cooperation and future trends

The governance of global health data requires cross-border collaboration. The World Health Organization (WHO), in its Global Strategy on Digital Health 2020–2025, emphasizes that digital health should promote global health equity. The WHO recommends that countries establish national digital health strategies to advance innovation and the large-scale adoption of digital health technologies. With the continuous maturation of technology and the gradual improvement of governance systems, the data-driven health economy will evolve from an “optional tool” into a “social necessity”, fostering a sustainable model of proactive health management for humankind [17-19].

7. Conclusion

Global health demands intensify and digital transformation accelerates, AI wearable devices are playing an increasingly vital role in the collection, processing, and application of health big data. These devices have evolved from simple fitness trackers into comprehensive “health managers” capable of analyzing data to reduce medical expenditures, optimize healthcare resource allocation, and drive the development of emerging sectors such as Insurtech and telemedicine.

However, challenges such as data privacy and security risks, widening health inequality, and the lack of data standardization and regulatory frameworks continue to hinder large-scale adoption. Low-income and elderly populations, in particular, face barriers to access due to low device penetration rates, preventing them from benefiting from data-driven health management.

To address these issues, policymakers and industry stakeholders must strike a balance between technological innovation and institutional development by improving data governance frameworks and strengthening international cooperation. As technology matures and governance systems evolve, the health big data economy will transform from a “voluntary option” into a societal necessity, driving a comprehensive upgrade of the global health economy and advancing humanity toward a sustainable, proactive health paradigm.

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