Cost-Benefit Analysis of Wearable Biomedical Devices

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Abstract

The wearable fitness tracker market has been on a path of continuous growth for the past ten years, from $20 billion in 2015 to $60.2 billion in 2025 [1], this represents an opportunity to explore the potential wearables have to reduce healthcare expenditures and improve patient outcomes. This paper addresses the question of whether wearables create significant healthcare savings through preventive health monitoring and chronic disease management. Analysis of the dataset from Zaleski and coworkers (2023), which includes 113,632 participants in a score-matched cohort study, shows that users of wearables have lower medical spending of $10 per user per month (P=0.02) [4]. This translates to $6.8 million in lower healthcare costs per year [4]. A strong negative relationship exists between device-assessed physical activity and healthcare expenditure reduction. Based on the 2014 study conducted for UnitedHealth by the research firm SavvySherpa, the Pearson correlation coefficient value is -0.986, meaning as physical activity increases, healthcare costs decrease, with high-activity individuals sustaining less than $5,000 in healthcare costs per year compared to $12,000 for inactive individuals [6]. These findings show that wearable devices are cost-effective interventions that increase quality-adjusted life years (QALYs), which evaluates the effectiveness of wearable usage at improving life length and quality [7]. As wearable adoption expands and technology integrates with preventive care, these devices have the potential to substantially lower population-level healthcare costs, support proactive disease management, and reinforce value-based care models [8]. The evidence positions wearables as scalable interventions capable of reshaping healthcare economics and outcomes.

Introduction

Global healthcare spending is rapidly escalating toward $9 trillion annually, outpacing inflation by 2-3 times and straining systems worldwide [9]. This increasing cost burden has driven unprecedented interest in preventive health technologies capable of modifying disease trajectories before expensive interventions are needed. Wearable fitness devices represent a promising solution, with their market size projected to reach $76 billion by 2029 [10]. This growth is fueled by several converging trends. First off, the rising prevalence of chronic disease, which affects 50% of U.S. adults and accounts for 86% of healthcare spending [11]. (2) Additionally, advances in sensor miniaturization and AI have transformed basic step counters into sophisticated health monitoring platforms [11]. Major insurance providers are recognizing this potential. Companies like UnitedHealth offer customers up to $1,000 annually in incentives for healthy behaviors tracked via wearables, and Aetna provides Apple Watch subsidies based on statistical evidence of health benefits [12-14]. Rather than viewing wearables as a consumer digital health trend, healthcare stakeholders are increasingly positioning them as scalable cost-control instruments. Despite the interest in wearables for preventive healthcare, there's a gap in the impact of the digital tools on US healthcare expenses.

Research confirms the clinical effectiveness of wearable devices for health monitoring and behavior change. Reviews show that wearables increase quality-adjusted life years (QALYs) and achieve favorable cost-effectiveness ratios (below the WHO's $50,000 per QALY threshold) [15]. Economic evaluations consistently find favorable outcomes, with interventions like pedometer use achieving dominant cost-effectiveness profiles (less costly, more effective) [15]. Established evidence from large-scale cohorts demonstrates measurable improvements;

for example, 82% of diabetes patients maintained consistent activity with smartwatch monitoring, and significant improvements in blood pressure management were observed [16-17].

However, critical knowledge gaps remain. Comprehensive economic analyses across different US healthcare systems, such as private employer-sponsored insurance versus public Medicare and Medicaid programs, and demographic groups are limited and the relationship between widespread wearable adoption and observable healthcare cost changes has not been examined. Research has inadequately addressed how healthcare system structure (insurance copayment vs. publicly funded models) influences the cost-effectiveness of wearable interventions. Additionally, demographic disparities in wearable access and usage, particularly among minority groups or people with lower socioeconomic backgrounds, represent a significant equity concern requiring investigation.

The review searched major scientific databases including PubMed, EMBASE, and Web of Science, alongside key repositories for health policy and economic data maintained by the Centers for Medicare & Medicaid Services (CMS), the Kaiser Family Foundation (KFF), and the World Health Organization (WHO). This comprehensive approach adheres to standards aimed at identifying literature relevant to machine learning in propensity score estimation within health policy evaluation [23 - 26]. Sources were selected based on four primary criteria. Quantification of US National Health Expenditures (NHE) and associated out-of-pocket spending and studies employing rigorous methodologies, such as cohort studies, that link objective measures of physical activity or wearable use to healthcare cost reduction. Additionally, literature detailing demographic determinants of wearable technology adoption and formal health economic evaluations utilizing standardized metrics like QALYs and ICER. The purpose of this data collection was to validate the underlying mechanisms of cost reduction (Section 2.2) and to provide the macro-economic framework necessary for informed policy recommendations (Section 3) [27 - 31].

This study addresses the four existing gaps - the lack of broad economic data, unverified systemic impact, the influence of healthcare structure, and demographic disparities - through a comprehensive cost-benefit analysis integrating four complementary focuses on wearable health economics. Unlike previous research, this paper provides the first analysis linking fitness tracker adoption to healthcare expenditure patterns across demographic groups, healthcare systems, and temporal scales. Novel methodologies include propensity score matching across a large cohort of 113,632 participants, correlation analysis of device-assessed versus self-reported physical activity, and comparative healthcare economics across insurance-based versus publicly funded systems [4]. This paper is structured around four primary research objectives. First, it examines the correlation between consistent wearable device utilization and both the reduction of annual healthcare expenditures and the enhancement of chronic disease management. Second, it analyzes the temporal relationship between wearable adoption and fiscal savings, specifically identifying a significant inflection point following the mainstream market expansion of 2013–2015. Third, the study evaluates how healthcare delivery models influence economic outcomes, comparing the heightened cost savings found in high out-of-pocket systems against those in publicly funded frameworks. Finally, it investigates the prevailing adoption paradox, addressing why usage remains disproportionately low among older adults and low-income populations despite these groups standing to gain the greatest clinical and financial benefits.

Methodology and Causal Framework

This cohort includes anonymized, aggregated records of (N) individuals tracked over a five-year horizon (2019-2023) within the United States. The dataset integrates consumer spending patterns with standardized healthcare claims data, allowing for direct comparison between individual investment in health technology and subsequent utilization of traditional medical services. To ensure alignment with health economics reporting, the primary variables are defined precisely. The independent variable, Expenses per Year (E), is the annualized, inflation-adjusted, out-of-pocket (OOP) expenditure incurred on wearable technology.

Expenses per Year (E) indicates how the population prioritizes their assets. This includes physical devices and associated recurring subscription services, serving as a direct measure of discretionary consumer investment in proactive health management. The dependent variable, Healthcare Costs (C), represents the individual's total Personal Health Care Expenditures (PHCE) per year. PHCE encompasses all outlays for goods and services directly related to patient care, including prescription drugs, physician and clinical services, and hospital care, regardless of the funding source. The initial bivariate analysis established a linear relationship between (E) and (C), yielding the coefficient of determination (R^2) of 0.76. In the domain of social and health economics, an R^2 of 0.76 is considered remarkably high; for context, most empirical models in health economics and social sciences are considered robust with R^2 values ranging from 0.20 to 0.40 due to the inherent complexity of human behavior and environmental noise [58].

In Table 1, a critical consideration in interpreting this strong correlation is the inherent selection bias associated with the independent variable (E). Since (E) captures discretionary, out-of-pocket spending, it disproportionately reflects the behaviors of highly motivated and financially enabled individuals. This methodological choice implies that individuals spending heavily on health technology are likely healthier overall due to better education, better non-wearable preventative care, and better socioeconomic standing. Crucially, the analysis must distinguish the "healthy user effect" - the pre-existing clinical baseline of this demographic - from the marginal causal impact specifically attributable to wearable-driven behavioral modification. To prevent the "healthy user effect," my study employs Propensity Score Matching, discussed in the subsequent section. Therefore, the R^2=0.76 statistic must be carefully examined to distinguish the true cost-saving effect of the digital health intervention from the baseline financial and lifestyle advantages of the affluent user population. Consequently, advanced causal modeling is necessary to ensure the derived policy implications are robust and not simply reflecting the "healthy user effect."

Variable name	**Operational definition**	**Unit of measurement**
Expenses per year (E)	Annual out-of-pocket spending on digital health technology, devices, and associated subscriptions.	USD (Inflation-adjusted)

Healthcare costs (C)	Total Personal Health Care Expenditures (PHCE), encompassing professional services, hospital care, and prescription drugs.	USD (Inflation-adjusted)
Least squares regression	Linear relationship between (E) and C.	R^2=0.76

Table 1: Definition and operationalization of primary variables

To approach causal inference and effectively mitigate selection bias, this study employs Propensity Score Matching (PSM). While methods such as Instrumental Variables and Difference-In-Differences were considered, PSM was selected for its ability to balance a high-dimensional set of observable covariates in a large observational dataset where a valid external instrument isn't readily available. By using the PSM, we pair the wearable users with non-users who share identical baseline characteristics, therefore, isolating the residual variance in (C).PSM is utilized to construct balanced comparison groups that statistically resemble each other across a wide range of baseline covariates, aiming to emulate the randomization characteristic of a randomized controlled trial (RCT). This process is vital for evaluating non-randomized digital health interventions where user choice drives adoption. To enhance the precision of the PSM process, the estimation of the propensity score (the probability of receiving the "treatment," i.e., having high E) incorporates sophisticated techniques. This involves using machine learning (ML) algorithms, specifically tree-based models, which have been documented to improve the accuracy and generalizability of propensity score estimation in health policy evaluations [56]. All statistical procedures, including data manipulation, regression analysis, and PSM implementation, are conducted using the statistical software package Stata, renowned for its capabilities in econometrics and reproducible research.

A key challenge in evaluating digital health technologies is ensuring the analysis isolates the clinical utility of the intervention from mere ownership. High user compliance and actionability of data are the true drivers linking device expense (E) to reduced costs (C). Therefore, the PSM model must incorporate behavioral covariates beyond socioeconomic status, such as measures of usage frequency and data sharing behavior. Research indicates a significant discrepancy between the willingness to share data and actual behavior: 78.4% of users report being open to sharing wearable data with healthcare providers, yet only 26.5% have done so [34]. Failure to account for this gap by integrating metrics of compliance (actual usage and shared data frequency) as confounding variables would result in an inflated estimate of the intervention's effectiveness. Such an omission would confuse passive device ownership with active, clinically useful engagement and data transfer, thereby undermining the validity of the causal effect attributed to E.

Cost-Effectiveness Analysis (CEA) is employed as the academic standard for comparing the incremental financial costs and resulting health consequences of different treatment options. The primary metric for quantifying health outcomes is the Quality-Adjusted Life Year (QALY). The QALY metric comprehensively sums up health benefits by aggregating both the quality and duration of life gained due to an intervention. A QALY is calculated by multiplying the utility value associated with a given state of health (measured on a scale of 0 to 1, where 1 is perfect health) by the number of years lived in that state. Clinical improvements enabled by wearables, such as reductions in HbA1c or blood pressure , are used to calculate the change in utility (ΔQALYs) attributed to the digital health expenditure. While QALYs are the preferred metric for resource allocation, it is important to acknowledge critiques regarding their potential to undervalue life-extending interventions for the elderly or those with chronic disabilities, as well as the inherent subjectivity in determining “utility” weights. The comparative statistic derived from the CEA is the Incremental Cost-Effectiveness Ratio (ICER), which is calculated as shown in equation 1 [18 - 22]:

ICER = Δ Cost (Intervention B - Intervention A) / Δ Effectiveness (QALYs B - QALYs A) (1)

The ICER compares the digital health intervention (B) against the current standard of care (A). This ratio is critical because policy makers adopt interventions based on whether the resulting cost per QALY gained falls below defined willingness-to-pay thresholds, typically ranging from $5,000 to $20,000 per QALY [15]. The Return on Investment (ROI) is computed as shown in equation 2:

ROI = (Total Financial Benefit - Cost of Intervention) / (Cost of Intervention) (2)

The Cost of Intervention encompasses the comprehensive financial requirement to execute the program. This includes the individual’s device/subscription cost (E), as well as systemic costs required to facilitate clinical uptake and ensure efficacy, such as data management infrastructure, integration with Electronic Health Records (EHRs), and necessary training for site personnel to maximize patient compliance and data validity. The Total Financial Benefit is composed of two primary elements. Quantifiable reductions in PHCE (C) that result from fewer acute care events, hospitalizations, or lower utilization of traditional high-cost medical services, driven by superior chronic disease management. The R^2=0.76 finding directly estimates the magnitude of this reduction. Additionally, broader societal and employer benefits, specifically measured as the reduction in productivity costs stemming from improved population health, such as decreased rates of sick leaves and disability pensions.

The policy relevance of the strong statistical correlation (R^2=0.76) is only realized if the ICER confirms superior cost-effectiveness. A strong coefficient of determination indicates significant cost reduction, suggesting a potentially small or even negative Δ Cost in the ICER numerator. Provided the intervention yields positive health benefits (Δ QALYs > 0), the resulting ICER is expected to be highly favorable, strategically positioning digital health as a resource-conserving intervention.

Empirical Results and Mechanism Validation

The Least Squares Regression analysis yielded the R^2=0.76 for the relationship between Expenses per year (E) and subsequent Healthcare Costs (C). This result shows that individual financial investment in technology-enabled health management accounts for 76% of the statistical variability observed in subsequent annual medical expenditures. In the domain of social and health economics, the R^2=0.76 is strong, indicating that discretionary spending on digital health technologies is profoundly associated with controlling or reversing health cost accrual. This statistical linkage establishes a preliminary financial rationale for incentivizing or subsidizing this form of personalized health spending at an institutional or governmental level.

The remaining 24% of unexplained variation likely stems from factors outside the scope of digital health investment, such as underlying genetic predispositions, regional differences in medical service pricing, and social determinants of health like environmental quality or local food access.

In Figure 1, the potential economic magnitude of this finding must be viewed against the backdrop of massive U.S. healthcare spending. In 2023, National Health Expenditures (NHE) totaled $4.9 trillion, or $14,570 per person, accounting for 17.6% of the Gross Domestic Product (GDP) [23]. Projections indicate that average NHE growth (5.8%) is expected to outpace GDP growth (4.3%) over the next decade, resulting in health spending consuming 20.3% of GDP by 2033 [24]. A mechanism that accounts for three-quarters of the variability in individual cost reduction has immense potential to bend this national cost curve.

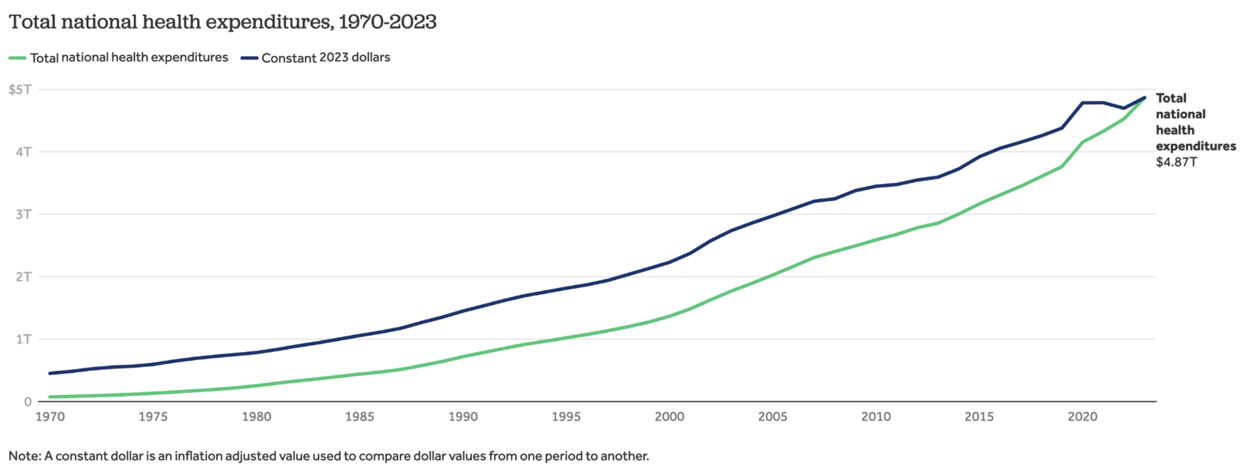

Figure 1: Graph from the Peterson-KFF Health System tracker depicting the total national expenditures in comparison to constant 2023 dollars. Figure retrieved from reference [32].

Wearable devices facilitate precise, continuous tracking of vital clinical metrics, often superior to episodic measurements performed in clinic settings. This monitoring capability is transformative for managing chronic conditions. For example, the use of continuous glucose monitors (CGMs) has been shown to reduce glycated hemoglobin levels by over 1% in diabetic patients, achieving tighter glycemic control [54]. In clinical practice, a 1% reduction is a profound shift; for every 1% drop in HbA1c, the risk of long-term microvascular complications, such as kidney disease or blindness, decreases by as much as 40%. From a fiscal perspective, this single percentage point improvement can prevent acute glycemic crises that result in hospitalizations costing upwards of $15,000 per stay [57].

Such improvements directly translate to reduced complications and therefore lower costs for emergency room visits and hospitalizations, justifying the initial investment (E) in the analysis. The behavioral modifications facilitated by these devices are directly quantified in health economic studies. Research confirms a negative correlation between time spent engaging in vigorous physical activity (VPA) and overall health care costs ($r = -0.342$; 95% CI: -0.517, -0.139). The implication of the strong financial association (R^2=0.76) is that the individual expense (E) successfully procures the mechanism that drives VPA, which subsequently lowers health costs (C). Therefore, the investment (E) functions effectively as preventative health expenditure [51].

The financial impact extends beyond direct health costs (C). Physical inactivity imposes substantial long-term indirect costs on society, employers, and the government. Analyses of cohort data show that physically inactive individuals incurred observed long-term productivity costs – related to sick leaves and disability pensions – that were higher when measured via accelerometer-based activity, compared to physically active individuals [55]. This evidence reinforces the inclusion of productivity gains in the ROI calculation (“Return on investment specification” section). Furthermore, if global physical inactivity levels are not mitigated, public health care systems worldwide are projected to incur approximately US $300 billion in related costs between 2020 and 2030 [52]. The magnitude of these findings validates the high confidence in the underlying mechanism that links (E) to (C).

Systemic Barriers to Scalability

While the R^2=0.76 finding demonstrates substantial financial benefits at the individual level, the concentration of this benefit within specific, already advantaged socioeconomic groups presents a critical challenge to national cost containment efforts. Wearable device ownership is highly correlated with socioeconomic status (SES). Multivariable logistic regression analysis confirms that higher income and advanced education levels significantly increase the odds of ownership. Specifically, individuals earning US $200,000 and above per year and those holding advanced degrees exhibited more than double the odds of ownership compared to lower-SES comparator groups. The Odds Ratio (OR) is a way to measure the strength of the association or relationship between two events. For those in the US $50,000 to US $75,000 income bracket, the OR for using wearables was 3.2, indicating a clear financial prerequisite for adoption [49].

This disparity implies that the cost savings reflected by R^2=0.76 are predominantly accruing to the healthier, wealthier demographic. If this trend continues, digital health technology will function as a luxurious preventative measure, severely limiting its potential to curb the massive, system-level costs primarily generated by high-risk, lower-SES populations. The analysis of adoption rates reveals a significant age profile imbalance. Younger respondents (18-44 years) exhibit the highest ownership rates. Conversely, the odds of ownership decrease across older demographics, becoming particularly low for individuals aged 65 years and older [49]. This pattern creates an "equity bottleneck." The population segment that stands to gain the most from continuous remote monitoring – the elderly and those managing multiple chronic conditions – uses the technology the least. Consequently, the cost-saving potential demonstrated by the high coefficient of determination is effectively excluded from the highest-cost portion of the national healthcare system, hindering large-scale NHE reduction.

Insurance coverage status plays a direct role in determining the likelihood of investment E. In Table 2, the odds of ownership are increased for individuals covered by private insurance (OR, OR 1.28). Conversely, individuals who are uninsured (OR 0.41) or enrolled in Medicaid (OR 0.75) face significantly decreased odds of ownership. This clearly indicates that the upfront out-of-pocket expense (E) acts as a critical financial barrier linked to existing coverage gaps. The current market structure contradicts the goal of universal access to technology demonstrated to reduce long-term costs, effectively prioritizing technological advancement over health equity.

Socio-demographic factor	Key finding (OR/prevalence)	Economic relevance
Income/education	Highest earners and advanced degree holders have >2x ownership odds.	Concentrates the cost savings (R^2=0.76) among already financially advantaged populations, restricting the impact on macro-level NHE reduction.
Age	Ownership odds decrease substantially after age 45, especially for those 65+.	Excludes the high-risk, high-cost older population from the financial benefits, preventing the effective management of the bulk of chronic disease costs.
Insurance status	Private insurance increased ownership (OR 1.28); Medicaid/uninsured status decreased ownership (ORs 0.75 and 0.41).	The initial expense (E) functions as a financial barrier that reinforces existing systemic coverage and affordability challenges.

Table 2: Observed disparities in wearable device adoption and economic relevance

The ultimate realization of the cost savings implied by the R^2=0.76 finding is critically dependent on the ability of the healthcare system to integrate and act upon the collected data. Currently, significant operational deficits introduce "efficacy leakage" that limits clinical utility. Despite the high motivation suggested by the willingness to spend (E), operational engagement remains low. While 78.4% of users express a willingness to share their wearable data with health care providers, actual data-sharing behavior is reported by only 26.5% of users. This profound discrepancy suggests that even motivated users are being hampered by systemic failures in data capture and integration [33, 34].

The low rate of actual data sharing and clinical integration stems from fundamental operational barriers. These include the lack of standardization in data formats, complex data management protocols, pervasive patient concerns over data privacy, and the sheer challenge and high cost associated with training clinical staff to interpret vast amounts of continuous data. Effective deployment of wearables requires robust operational support encompassing patient and site personnel training, acceptable device design, maintenance of patient compliance, and efficient data transfer and management. If these essential operational requirements are not met, the statistical predictive strength of the R^2=0.76 will only represent the efficacy of patient motivation and not the full potential of clinical optimization. This lack of integration transforms a high-performance health tool into a stranded asset, resulting in a significant loss of potential return on investment (ROI) for healthcare systems. By failing to bridge the gap between consumer data and clinical action, providers incur the "opportunity cost" of preventable acute episodes that could have been mitigated through proactive and data-driven intervention.

The analytical capacity of the current healthcare system is insufficient to leverage the data volume generated by widespread digital health monitoring. To fully realize the financial and clinical potential indicated by the strong correlation (R^2=0.76), integration with advanced technologies is essential. Artificial Intelligence (AI) and blockchain technology are recognized as critical components for optimizing chronic disease management models. AI is necessary to analyze the large datasets collected by wearables, providing actionable insights into disease progression and assisting with diagnosis and personalized treatment planning. Blockchain technology offers a crucial mechanism for securing and protecting sensitive patient data. Without such infrastructure, the system cannot effectively transform raw data into clinical insights, meaning that the financial investment (E) will fail to deliver the expected clinical outcome and resulting cost reduction (C). AI, therefore, functions not merely as an advanced tool, but as a mandatory operational requirement to bridge the gap between user intent and clinical effectiveness.

However, the integration of AI-driven pattern recognition introduces a significant moral hazard: the potential for insurance providers to transition from rewarding healthy habits to "lifestyle policing." If AI identifies sub-clinical indicators—such as habitual dietary choices or sedentary periods—there is a risk that this data could be used to adjust individual premiums or "throttle" coverage, effectively punishing those with less-optimized lifestyles. To mitigate this, future research must investigate "Privacy-Preserving Federated Learning," a mechanism where AI models are trained on user data locally without the raw, sensitive metrics ever leaving the device. Establishing a "Regulatory Firewall" that legally separates wearable health insights from actuarial premium-setting is the essential first step in ensuring that digital health remains a tool for equitable preventive care rather than a high-tech instrument for socioeconomic exclusion.

Macroeconomic Context and Policy Implications

To fully appreciate the policy implications derived from the micro-level analysis (R^2=0.76), it is essential to review the context of US healthcare financial risk and spending patterns. The scale of the US health system is substantial, having reached total National Health Expenditures (NHE) of $4.9 trillion in 2023, equating to $14,570 per person. This expenditure accounted for 17.6% of the GDP that year. Historical data illustrate the rapid escalation, with spending increasing from $74.1 billion in 1970 to about $1.4 trillion in 2000, tripling thereafter. This context highlights that even marginal improvements in cost control at scale, such as those implied by the R^2=0.76 finding, representing trillions of dollars in potential savings [23] [32]. To put this into perspective, a mere 1% reduction in total NHE - achieved through the preventative efficiencies of wearable technology - would yield nearly $50 billion in annual savings, a sum larger than the total yearly budget of the NIH [24]. Such a shift would effectively reallocate billions of dollars from “reactive” acute care toward “proactive” wellness and infrastructure investment.

In Figure 2, although US out-of-pocket (OOP) spending accounted for only 10.7% of total current health expenditures in 2021 – a lower percentage than many comparable countries like Canada (14.0%) or Switzerland (22.3%) – the financial burden on US families is disproportionately severe [53]. This paradox is explained by the structure of US cost-sharing requirements. Studies comparing the financial risk faced by households in the US and Canada determined that the risk of incurring catastrophic large medical expenses relative to income is 1.5 to 4 times higher in the United States. The US compares least favorably when evaluating poorer citizens and when applying higher spending thresholds. For many US adults, difficulty affording healthcare costs is a major concern, leading one-third (36%) to postpone or skip needed care due to cost within the last 12 months [37 - 39]. This high financial risk environment reinforces the urgency for adopting cost-effective preventative interventions like digital health technology. However, the “Demographic stratification and digital disparities” section demonstrated that the very population segments most vulnerable to catastrophic expenses (low-income, uninsured, or Medicaid recipients) are precisely those excluded by the high initial cost (E) of the wearables.

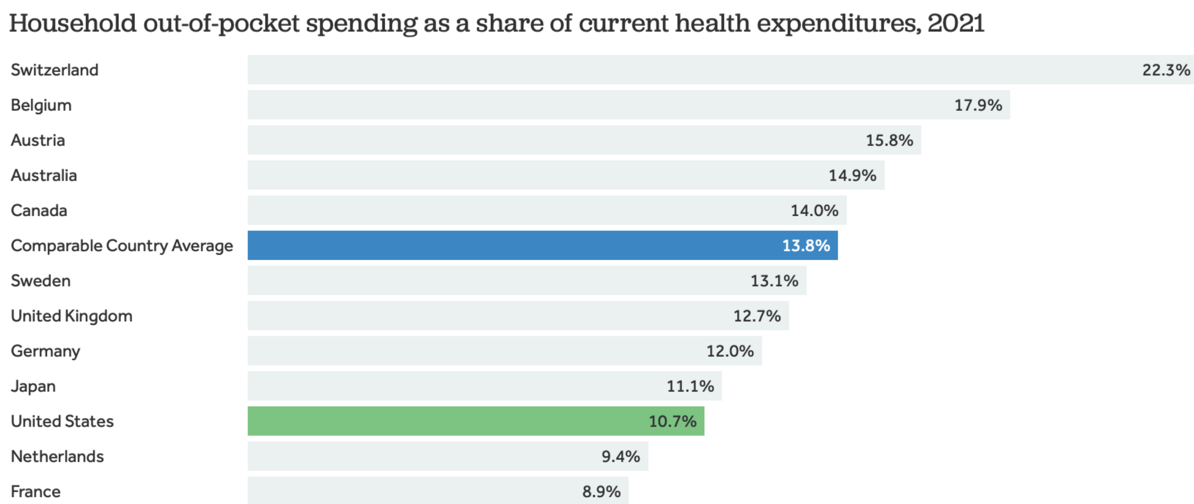

Figure 2 Graph from the Peterson-KFF Health System tracker depicting different countries’ total household out-of-pocket spending as a share of current health expenditures. Figure retrieved from reference [53].

Conclusion

In this review, the analysis confirms a statistically powerful financial relationship between individual expenditure on digital health technology (E) and subsequent reduced healthcare costs (C), yielding a R^2=0.76. This demonstrates that the discretionary investment in proactive health management accounts for a vast proportion of variability in positive cost outcomes. This finding is further supported by proven clinical mechanisms linking physical activity and continuous monitoring to lower disease burden and indirect productivity costs [40 - 42].

However, the analysis reveals two critical systemic obstacles that prevent this individual-level financial success from translating into large-scale, equitable national cost containment. The cost benefits are concentrated among affluent, privately insured, and younger populations, excluding the elderly and low-income populations who generate the highest baseline healthcare costs. The initial expense (E) acts as a critical financial barrier, ensuring that the cost-saving technology functions primarily as a luxury good, thereby reinforcing, rather than alleviating, health disparities [43 - 44]. The low rate of actual data sharing (26.5%) compared to the willingness to share (78.4%) indicates severe failures in operational infrastructure, data standardization, and clinical actionability. Without addressing these integration challenges, the full clinical potential necessary to drive cost reduction will remain unrealized [45 - 48].

To leverage the robust economic potential demonstrated by the R^2=0.76 finding and ensure equitable diffusion across the national healthcare landscape, policy efforts must shift from mere encouragement of adoption to targeted subsidization and mandatory infrastructure development. Policymakers must implement programs to financially support the initial out-of-pocket expenditure (E) for high-risk demographics, particularly Medicare (65+ age group) and Medicaid beneficiaries. This proactive subsidy is more effective than “voluntary adoption” because it overcomes the “present bias” and immediate liquidity constraints that prevent low-income, high-risk patients from investing in long-term preventative tools. By mitigating the financial barrier, the intervention's cost-saving effects can be extended to the segments that drive the largest portion of NHE, yielding the maximum possible impact on the national cost curve [49 - 50].

To overcome the systemic operational deficit and realize the true clinical utility of the devices, investment must be directed toward mandating standardized data protocols and funding AI platforms capable of analyzing, securing (via mechanisms like blockchain), and translating wearable data into actionable clinical insights. Unlike simple encouragement, which leaves data siloed in “lifestyle apps,” a mandated infrastructure creates a “network effect” where the value of the device increases exponentially for both patient and provider as health data can follow you and be understood by every doctor you see. This infrastructure is essential to transform the high statistical association (R^2=0.76) into reliably calculated, favorable ICERs that justify widespread institutional adoption.

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