

# Wearable Health Technology Adoption: A Social Cognitive Analysis of Pre- and Post-COVID-19 Behavior

Lavlin Agrawal

 <http://orcid.org/0000-0001-8877-2336>

*North Carolina Agricultural and Technical State University, USA*

Pavankumar Mulgund

 <http://orcid.org/0000-0001-8434-5070>

*University of Memphis, USA*

Richelle Oakley DaSouza

 <http://orcid.org/0000-0003-4294-6286>

*North Carolina Agricultural and Technical State University, USA*

Srikanth Venkatesan

*University of Memphis, USA*

Pankaj Chaudhary

*North Carolina Agricultural and Technical State University, USA*

**Received:** October 10th, 2025 | **Accepted:** April 30th, 2026

## ABSTRACT

The COVID-19 pandemic accelerated the adoption of wearable health technologies (WHTs), reshaping patterns of use and motivations. This study applies Social Cognitive Theory and Digital Divide frameworks to compare pre- and post-pandemic determinants of WHT adoption using survey-weighted logistic regressions and subgroup analyses by race and gender. Findings show that while personal agency and social context remain relevant, structural factors such as smart device ownership, insurance coverage, and digital health integration became more decisive after the pandemic. The influence of education declined, and income-based disparities widened, signaling a shift from skill-based divides to access-based divides. Demographic trends remained stable, although health-risk salience increased and equity patterns diverged. The results suggest that motivation and confidence alone are insufficient to influence WHT adoption. Material access and digital infrastructure now play a central role. Implications are discussed for temporally sensitive IS theory and inclusive technology design and policy.

## KEYWORDS

Wearable Health Technology, COVID-19, Social Cognitive Theory, Digital Divide, HINTS, Technology Adoption, Social Reinforcement, Health Informatics

## INTRODUCTION

Wearable health technologies (WHTs) have evolved from being niche fitness gadgets into being integral components of contemporary digital health ecosystems. Devices such as Fitbit, Apple Watch, and Garmin trackers now monitor a wide range of physiological indicators, including activity levels,

DOI: 10.4018/JDM.409547

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

sleep patterns, heart rate, and oxygen saturation, and some are capable of detecting conditions such as atrial fibrillation that require clinical follow-up (Perez et al., 2019; Piwek et al., 2016). At the same time, healthcare organizations are increasingly incorporating patient-generated health data (PGHD) into electronic health records (EHRs), clinical dashboards, and patient portals and expanding remote patient monitoring programs that rely on wearable data (Steinhubl et al., 2015). Major technology and healthcare platforms—including Apple Health integrations and Epic patient portals—now support the incorporation of wearable data into routine clinical workflows, enabling clinicians to access PGHD alongside traditional clinical records (Steinhubl et al., 2015). These developments reflect a broader shift toward remote patient monitoring, continuous health tracking, and digitally mediated healthcare delivery (Bardhan et al., 2025; Steinhubl et al., 2015).

The COVID-19 pandemic accelerated these transformations as healthcare providers rapidly expanded telehealth services and remote monitoring programs to maintain continuity of care (Keesara et al., 2020; Mann et al., 2020). Consequently, wearable devices and connected health applications became important tools for individuals seeking to track symptoms, manage chronic conditions, and maintain engagement with healthcare providers (Keesara et al., 2020). For healthcare providers, technology firms, and policymakers, this rapid shift raised important questions regarding who adopts these technologies and how adoption drivers may evolve as healthcare becomes increasingly digitally mediated (Agarwal et al., 2010; Ghose et al., 2022). Despite extensive research in information systems (IS) on technology adoption—including foundational models such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT; Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012)—there remains a limited understanding of how major environmental disruptions reshape the relative influence of behavioral, social, and structural determinants of WHT adoption.

To address this gap, this study applies social cognitive theory (SCT) and the digital divide (DD) framework to examine how determinants of WHT adoption changed before and after the pandemic. SCT emphasizes personal agency and highlights the reciprocal relationship between cognitive factors (e.g., self-efficacy), behavior, and environmental influences such as social modeling and reinforcement (Bandura, 1986). In contrast, the DD framework focuses on inequalities in access to digital resources, skills, and outcomes, extending beyond simple connectivity to include second- and third-level divides in capabilities and benefits (Ragnedda & Muschert, 2013; van Dijk, 2006). Integrating these perspectives allows us to examine both the psychological processes that motivate technology use and the structural conditions that enable or constrain participation in digital health ecosystems, an issue that consumer health informatics scholars warn may intensify as digital health expands (Veinot et al., 2018).

Using two cross-sectional waves of the Health Information National Trends Survey (HINTS), a nationally representative survey conducted by the United States National Cancer Institute, we estimate logistic regression models predicting WHT adoption before and after the pandemic. This design enables the comparison of key behavioral and structural factors—including digital health navigation experience, online health group participation, smart device ownership, patient portal use, health status, education, income, and anxiety—between 2020 and 2022. The results indicate continuity in key SCT constructs: self-efficacy (digital health navigation experience) and social reinforcement remain associated with adoption across both periods. At the same time, several structural predictors shift in importance. For example, education becomes less predictive in 2022, potentially reflecting the broader diffusion and usability of wearable technologies as markets mature (Meskó et al., 2017; Piwek et al., 2016). Conversely, indicators of digital infrastructure—such as smart device ownership and engagement with online health platforms—appear increasingly important, consistent with the deeper integration of wearable technologies into telehealth and remote monitoring ecosystems following COVID-19 (Keesara et al., 2020; Steinhubl et al., 2015). Health-related factors also show changes, with overweight status emerging as a stronger predictor in 2022, which may reflect heightened health awareness and risk-management behaviors following the pandemic (Patel et al., 2015).

34 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: [www.igi-global.com/article/wearable-health-technology-adoption/409547](http://www.igi-global.com/article/wearable-health-technology-adoption/409547)

## Related Content

---

### Which Way to Go for the Future: The Next Generation of Databases

(2018). *Bridging Relational and NoSQL Databases* (pp. 311-328).

[www.irma-international.org/chapter/which-way-to-go-for-the-future/191987](http://www.irma-international.org/chapter/which-way-to-go-for-the-future/191987)

### Matching Relational Schemata to Semantic Web Ontologies

Polyxeni Katsioui, Petros Papapanagiotou, Vassileios Tsetsos, Christos Anagnostopoulos and Stathes Hadjiefthymiades (2009). *Handbook of Research on Innovations in Database Technologies and Applications: Current and Future Trends* (pp. 434-442).

[www.irma-international.org/chapter/matching-relational-schemata-semantic-web/20728](http://www.irma-international.org/chapter/matching-relational-schemata-semantic-web/20728)

### An Infodemiological Analysis of Google Trends in COVID-19 Outbreak: Predict Case Numbers and Attitudes of Different Societies

Adem Doganer and Zuopeng (Justin) Zhang (2021). *Journal of Database Management* (pp. 1-19).

[www.irma-international.org/article/an-infodemiological-analysis-of-google-trends-in-covid-19-outbreak/276496](http://www.irma-international.org/article/an-infodemiological-analysis-of-google-trends-in-covid-19-outbreak/276496)

### Similarity Learning in GIS: An Overview of Definitions, Prerequisites and Challenges

Giorgos Mountrakis, Peggy Agouris and Anthony Stefanidis (2005). *Spatial Databases: Technologies, Techniques and Trends* (pp. 294-321).

[www.irma-international.org/chapter/similarity-learning-gis/29669](http://www.irma-international.org/chapter/similarity-learning-gis/29669)

### An Efficient NoSQL-Based Storage Schema for Large-Scale Time Series Data

Ruizhe Ma, Weiwei Zhou and Zongmin Ma (2024). *Journal of Database Management* (pp. 1-21).

[www.irma-international.org/article/an-efficient-nosql-based-storage-schema-for-large-scale-time-series-data/339915](http://www.irma-international.org/article/an-efficient-nosql-based-storage-schema-for-large-scale-time-series-data/339915)